OPTIMIZATION OF SAGD AND VAPEX PROCESSES WITH MINIMUM WELL SPACING CONSTRAINTS

BY

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To my beloved Ammi (mother), Abbu (father), family and friends whom encouragement and support helped me throughout my stay in KFUPM

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LIST OF ABBREVIATIONS

EOR	Enhanced Oil Recovery
SAGD	Steam Assisted Gravity Drainage
VAPEX	Solvent Vapor Extraction
PSO	Particle Swarm Optimization
NPV	Net Present Value
WPO	Well Placement Optimization
WCO	Well Control Optimization
COP	Constraint Optimization
MINLP	Mixed Integer Non Linear Programming
cSOR	Cumulative Steam Oil Ratio

ABSTRACT

Full Name : Rizwan Ahmed Khan

Thesis Title : Optimization of SAGD and VAPEX Processes using Horizontal Well Placement with Minimum Spacing Constraint

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Steam Assisted Gravity Drainage (SAGD) and Solvent Vapor Extraction (VAPEX), both of the techniques have been proved to be successful for the exploitation of heavy oil reservoirs. Field development of heavy oil reservoirs requires careful determination of optimal parameters; well locations and control setting of producer and injector. In recent years, field development decisions based on sensitivity studies have been shifting towards automated optimization. The optimization technology has aided the enhancement in decision making process. However, the optimization tools rarely enforce well spacing constraints during the optimization process.

In this research, we intend to study the well spacing constraint for horizontal well placement optimization problem. We proposed the methodology to solve the horizontal well placement optimization problem constrained to any defined minimum well spacing. The minimum spacing must be user defined between any two wells to ensure drilling hazards. The inequality constraints for well spacing are defined and penalty approach is implemented to solve

the constraint optimization problem. The Particle Swarm Optimization (PSO) was used as an optimizer to determine the optimum parameters.

In this project, we present the optimal parameter selection for Steam Assisted Gravity Drainage (SAGD) and Solvent Vapor Extraction (VAPEX). We performed the search of optimum parameters in three cases. In the first case, we find the best well pair locations for both SAGD and VAPEX process. In the second case, the well control and well placement are optimized simultaneously. In the third case, the vertical separation between injector and producer, well controls and well placement all together are optimized. Also, we compared the performance of both SAGD and VAPEX processes in the optimization problem.

The results indicate that the method can successfully determine the optimal parameters while satisfying the constrained imposed by the user. The comparison of results shows the better performance of SAGD over VAPEX in Case 2 and Case 3, while VAPEX shows good results in Case 1.

ARABIC ABSTRACT

ملخص الرسالة

الاسم: رضوان أحمد خان

عنوان الرسالة: استمثال عمليتي التصريف بالتثاقل المعتمد على البخار (SAGD) والاستخلاص بواسطة البخار المذيب (VAPEX) بواسطة استخدام عملية مباعدة الأبار الأفقية بأقل قيود مباعدة

التخصص: هندسة البترول

تاريخ الدرجة العلمية: ديسمبر 2015م

التصريف بالتثاقل المعتمد على البخار (SAGD) و الاستخلاص بواسطة البخار المذيب (VAPEX)، كلتا التقنيتان اثبتتا نجاحهما في الإنتاج من مكامن النفط الثقيل. يستخدم زوج من الأبار الأفقية إحداهما منتجة والأخرى تستخدم للحقن لإنتاج النفط الثقيل، تعمل الجاذبية الأرضية كقوة دافعة للتقليل من لزوجة النفط. الإنتاج من مكامن النفط الثقيل أصبح ممكناً وفعالاً بواسطة تطبيق تقنية الأبار الأفقية التي تنتج عن تحسين توصيلية وأداء المكمن. تتطلب عملية تطوير الحقل من مكامن النفط الثقيل تصميماً دقيقاً لتحديد العناصر الأمثل مثل مواضع الأبار وخصائص التحكم للبئر المنتجة والبئر الحاقنة. العدد الكبير للمتغيرات المتوقعة بجانب حالة عدم التيقن التام بجيولوجية المكمن، تجعل من عملية تصميم خطة أمثل لتطوير الحقول أمراً معقداً. في السنوات الأخيرة، أصبحت قرارات تطوير الحقول التي تعتمد على دراسات تحليل الحساسية تتجه نحو الاستمثال الآلي. ساعدت تقنية الاستمثال في تحسين عملية إتخاذ القرار، ومع ذلك فإن أدوات الاستمثال نادراً ما تطبق في عملية وضع قيود لمباعدة الأبار خلال عملية الاستمثال. في بعض الحالات، أظهرت النتائج المثلى أن عملية تهيئة البئر تتطلب صافي عالي للقيمة الحالية (NPV) لكن بتمثل ذلك في قصور في عملية وضع الأبار.

في هذا العمل، طبقنا بنجاح وضع قيود لعملية مباعدة الأبار الأفقية في عملية الاستمثال. قدمنا منهجية لحل مشكلة استمثال وضع الأبار الأفقية مقيدةً بأي مباعدة معلومة لهذه الأبار. عملية المباعدة بين بئرين يفترض أن تكون معرّفة بواسطة المستخدم لتأكيد مخاطر الحفر. القيود المتفاوتة لعملية مباعدة الأبار يجب أن تعرف ولابد من تطبيق نهج جزائي لحل مشكلة استمثال القيود. تم استخدام عملية استمثال عناصر السرب (PSO) كمستمثل لتحديد العناصر المثلى لكل الحالات الثلاث.

في هذه الرسالة، قدمنا عملية اختيار عنصر مثالي لعمليتي التصريف بالتثاقل المعتمد على البخار (SAGD) و الاستخلاص بواسطة البخار المذيب (VAPEX). أجرينا بحثاً عن تلك العناصر في ثلاث حالات. في الحالة الأولى، نجد عن أفضل موضع لزوجي الأبار لكلتا العمليتين (SAGD) و (VAPEX). أما في الحالة الثانية، تم الاستمثال لتحديد وضع الأبار والتحكم بالأبار أنياً. وفي الحالة الثالثة، تم الاستمثال لكل من مسافة الفاصل العمودي بين البئر المنتجة والبئر الحاقنة، تحديد وضح الأبار والتحكم بالأبار كلها معاً. أيضاً، قارنا أداء كلاً من عمليتي (SAGD) و (VAPEX) في عملية الاستمثال.

أشارت النتائج إلى أن هذه الطريقة يمكنها بنجاح تحديد العناصر المثلى في حين فرض المباعدة يتقيد بواسطة المستخدم. أظهرت مقارنة النتائج أن الأداء كان أفضل لعملية (SAGD) على (VAPEX) في الحالة الثانية والثالثة، بينما أظهرت عملية (VAPEX) نتائج جيدة في الحالة الأولى.

CHAPTER 1

INTRODUCTION

With increasing demand for hydrocarbons in the world, it is important to utilize all the possible tools and techniques to produce maximum hydrocarbon from the sub-surface. The global attention gain by unconventional resources is due to its huge number of Original Oil in Place, OOIP. The heavy oil resources comprise of over six trillion barrels, nearly three or four times of the conventional original oil in place (OOIP) in the world (IEA, 2014). However, high-viscosity and high-density fluid pose numerous operational and economic challenges to produce from the reservoir. The advancement in EOR technology is able to cater this issue. Furthermore, the improvement in reservoir characterization and formation evaluation methods; reservoir modelling and simulation techniques; and reservoir management strategies significantly upturn the ultimate recovery.

1.1 Enhanced Oil Recovery (EOR)

EOR is defined as the techniques that are implemented in order to increase the oil recovery from reservoirs after primary and secondary recovery. EOR may involve the injection of substances in the reservoir that alter the reservoir rock and fluid properties.

EOR techniques are broadly categorized as gas injection (miscible) methods, thermal methods and chemical methods. These three broad categories are further divided into main categories as shown in Figure 1.

The type of EOR technique to be implemented in a field or reservoir is based on certain selection criteria. The selection criteria may include parameters like reservoir pressure, reservoir temperature, depth, average permeability, net thickness, formation type, API gravity and viscosity of the crude oil. The decision of implementing an EOR technique depends on the extent of how much the reservoir characteristics matches the selection criteria. It also depends on the availability of resources and feasibility of a particular technique. EOR technique production detailed of worldwide is shown in the Figure 2 .

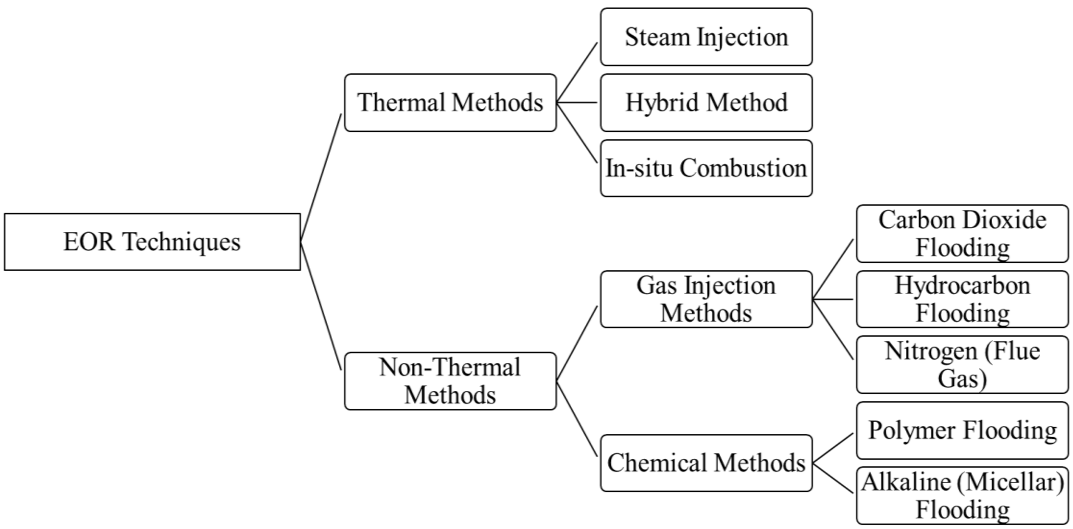


Figure 1: Classification of enhanced oil recovery techniques

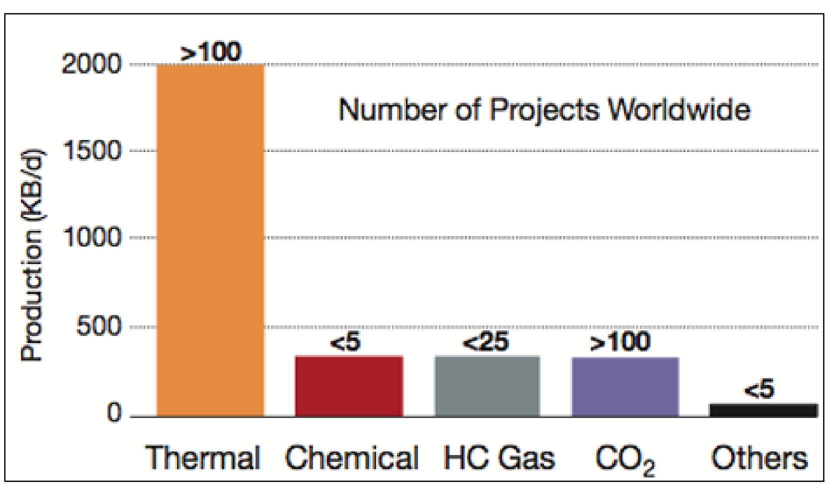


Figure 2: World oil production volumes by various EOR methods (SPEJ, 2010)

1.1.1 Thermal Flooding

The most widely used EOR technique is thermal flooding, which currently constitutes the largest portion of EOR oil production. Thermal methods can be broadly characterized as steam flooding, hot water, in situ combustion, and hybrid (combination of steam and solvent). Mainly, thermal methods are valid in reservoirs having heavy oils, however miscible and chemical flooding are functional in light or medium oil reservoirs.

Typically, the relationship between heavy oil viscosity and temperature is shown in Figure 3. As can be seen, viscosity decreases exponentially with a small rise in temperature of almost 100–200 ˚F. The reservoir temperature can be increased by generating thermal energy in situ by combustion of oil or by injection of hot fluid.

Thermal recovery mechanisms of oil include (1) fall in the heavy oil viscosity leads to reduction in flow resistance close to well bore and (2) the increases in temperature causes the decrease in gas solubility with the improvement in solution gas drive mechanism.

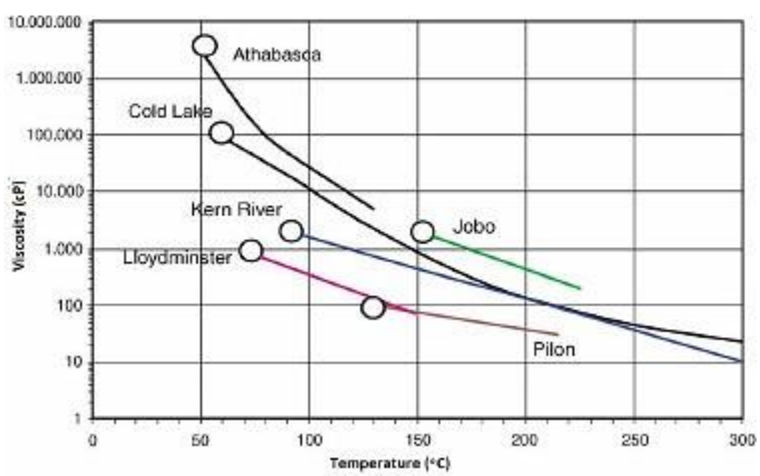


Figure 3: Typical viscosity-temperature relationships for heavy oil (Farooq Ali, 2003)

Reservoir characteristics of a typical heavy oil deposits are (Taber et al., 1996):

- Shallow depth (less than 3000 ft.)
- Formation thickness (50 ft. to many hundred feet)
- High porosity (around 30 %)
- High permeability (one to several darcies)
- Oil saturation (pore volume of 50-80 %)
- Viscosity (greater than 1000 cp)
- Oil Gravity (less than 20)

1.1.1.1 Steam Assisted Gravity Drainage (SAGD) and Vapor Extraction Process (VAPEX):

The progression in horizontal well technology facilitated to develop and produce heavy oil reservoirs by very promising recovery methods such as Steam Assisted Gravity Drainage (SAGD) and Solvent Vapor Extraction (VAPEX).

Steam-Assisted Gravity Drainage (SAGD) technique is a technically effective process to extract heavy oil from reservoirs. This process has been successfully executed in different projects to recover heavy oil across the world. Solvent Vapor Extraction (VAPEX) technique is emerging as an alternate method to extract the heavy oil, however it has not been tested at field scale. This process is the modified form of SAGD in which solvents is injected as injection fluid instead of steam. In both methods, injection fluids are injected into the reservoir by an injector, injection fluid dilutes the oil and allow gravity to assist it to flow towards the lower well and displaced oil is extracted from a producer positioned underneath the injector, both wells are horizontal in nature and parallel to each other. In the process of SAGD, the injection fluid (steam) transfer heat into heavy oil to dilute it while in VAPEX process, injected solvents vapors dissolve in bitumen at the interface between solvent and heavy oil and diffuses into bitumen and dilutes the oil. The schematic of SAGD or VAPEX chamber is presented in Figure 4.

Despite the higher oil recovery of the SAGD method, there are several challenges associated with this technique including the requirement of large amount of fresh water, produced water treatment and handling, and huge energy consumption to generate steam, resulting in high CO2 emissions. On the other hand, there are also many challenges in VAPEX, including the requirement of large amount of solvent and losses of solvent in the reservoir. In addition, although VAPEX is less energy intensive than SAGD, it produces at lower rates. The optimal placement of wells define the propagation of steam or solvent within the reservoir and resulting the dilution of oil flow towards the producer. The performance of both methods are critically dependent on the well location and operating conditions. Thus, it is essential to define the optimum well location along with corresponding operating conditions to yield maximum economic returns.

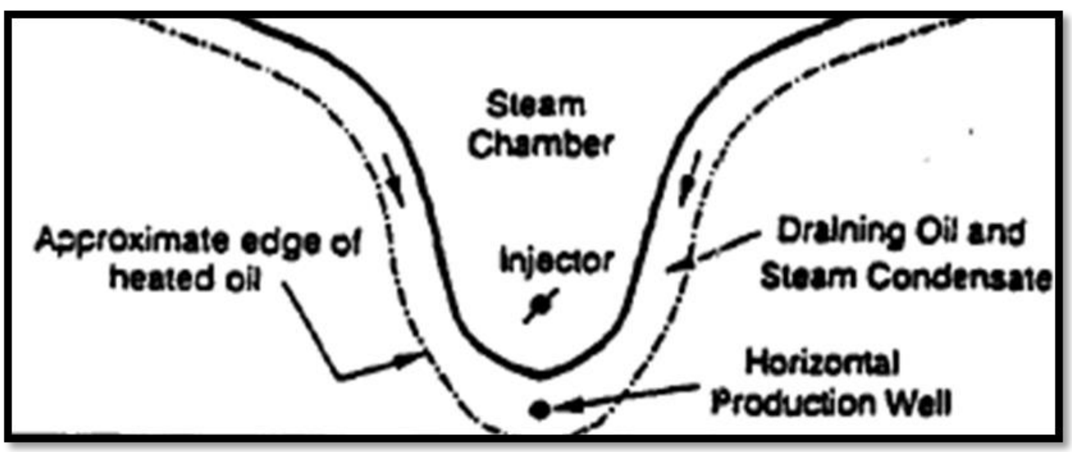


Figure 4: Depicts the steam/vapor chamber formation in SAGD/VAPEX process.

Since the geological complication and the problem nature are nonlinear, intuition is not adequate to promise the finest well placement in most cases. Similarly, the typical use of sensitivity analysis to assess the different scenarios would hardly succeed to deliver an optimal solution in the complex problem. The problem is more daunting under the influence of uncertainty in the geologic description of the reservoir. Consequently, an optimization routine to assess the performance and feasibility of multiple well placement positions is the need of the hour. The industry is shifting from traditional/intuition based optimization to automated optimization algorithms.

While planning field development plan reservoir management team considers minimum well spacing as a crucial component of well placement procedures to avoid interference in the drainage area of existing well. Despite the crucially importance of well spacing in well placement optimization, most of technical papers on well placement optimization do not address this issue. The main objective of this research is to devise a field development for heavy oil field with the enforcement of minimum spacing constraint. The optimization parameters are well location, well length, and well rates.

With the increasing interest of industry to focus unconventional reservoirs, the research in this area needs attention. After the screening process of thermal EOR mechanism for the field the next step is to optimize the process.

A literature review of the well placement optimization procedures along with its application in heavy oil reservoir and an introduction of the research completed in SAGD and VAPEX processes are presented in chapter 2.

Chapter 3 mentions the statement of the problem, and research objectives.

Chapter 4 discusses the theoretical background of the stochastic algorithm used in this research, formulation of the problem, and solution approach.

Chapter 5 presents the results and discussion, the results of all cases are discussed and compared on the basis of objective function.

Chapter 6 gives the conclusions of the thesis.

CHAPTER 2

LITERATURE REVIEW

This chapter presents the work that has been carried out in well placement optimization within different reservoir development context. Further, it also highlights the research in the heavy oil exploitation with SAGD and VAPEX techniques. The application of well placement optimization in heavy oil reservoirs is the underlying target of the study. Well placement optimization have been studied by many researchers and they covered different aspects of placement, with both gradient based and derivative free approaches of optimization. The use of different algorithms, optimization techniques and helper methods have been studied by different authors. Also, the effect of the uncertainties in the well placement optimization have been studied and different ways to deal with the geological uncertainty is presented in the literatures. Different evaluation tool as objective functions have been used in the literature. Some recent work discussed the joint optimization of well placement and well control optimization, and some authors addressed the use of multiobjective optimization.

Steam Assisted Gravity Drainage (SAGD) and Solvent Vapor Extraction (VAPEX) processes have been discussed by many authors to understand the physics of the fluid flow in the porous media. Most of the previous work has focused on the experimental side of the process and how it is affected by different mechanisms. Also, some work has been done on the simulation study of the process, and few studies have addressed the optimization of well control in SAGD and VAPEX process.

The motivation of this study is to recognize the absence of the aforementioned elements in the present literature and understand how the given gap can be abridged.

2.1 Review on Well Placement and Control Optimization

Rian and Hage (1994) presented the main method for automatic optimization of well locations, for that purpose they used a numerical simulator. They have illustrated the computational barriers in the optimization of conventional full scale models that cause due to the requirements of number of simulations, so they introduced a fast front-tracking simulator as the evaluation tool and also define the limitations of that simulator.

Beckner and Song (1995) worked for the problem of well placement, they applied the traveling salesman framework by using Simulated Annealing (SA) that helped to find the finest locations of the wells. The location and scheduling of 12 wells were optimized with the limitation of fixed orientation and length.

Aanonsen et al. (1995) used a response surface methodology, incorporating experimental designs and a kriging proxy for optimization of wells locations under uncertainty.

Bittencourt and Horne (1997) merged the GAs with the polytope method for the development of a hybrid genetic algorithm (bGA), to gain the advantage from the best attributes of each method. The polytope method looks for the finest solution by making a simplex with a number of vertices equivalent to one or more than the dimensionality of the search space. Each one of the vertices is evaluated and the method guides the search by reflecting the worst point around the centroid of the remaining nodes. This algorithm strived for the optimization of the well placement in a faulted reservoir and they also tried to improve three parameters for all the four wells: well type (which tells that whether the well is horizontal or vertical), horizontal well orientation and well location. In the optimization algorithm economic analysis incorporated with few practical designs considerations is also studied.

Pan and Horne (1998) used multivariate interpolation methods such as kriging and least squares as proxies to predict the result of reservoir simulation. The purpose of the first algorithm is to construct a function that has a simple known form to approximate some objective function. The behavior of this objective function is first observed through a number of simulations. Then, a function is constructed such that it minimizes the sum of the squared residual between data and the function values. To begin their study, they selected several well locations for numerical simulation as a sample to train the proxy. Then, net present value (NPV) surface maps were generated using the two proxies. These maps were subsequently used to estimate objective function values at new points. They observed that the Kriging method provides more accurate means to estimate the objective function than the Least Squares interpolation in the tested examples.

Guyagular and Horne (2000) enforced the hybrid optimization algorithm, also integrated the bGAs features with polytopes method. Kriging and Artificial Neural Networks (ANN) act as a helper functions which serve as proxies to reduce the cost of reservoir simulations. They were trying to explore patterns in data and to model complicated connection between inputs and outputs, when the teaching phase of the network that includes creating a database from several simulation runs, will complete. Location of number of vertical injectors was enhanced by this study for a waterflood projects with the net present value (NPV) as an evaluation tool. Conclusion given by Guyagular et.al was that Kriging was an excellent proxy as compared to neural networks for proved problems. The uncertainty assessment of study was also directed by them which was based on the framework of decision theory. As a part of their study, a comprehensive sensitivity analysis was conducted to define the effect of the GA parameters.

Montes et al. (2001) studied the hybrid free optimization of vertical well placement using a genetic algorithm (GA). Genetic algorithm parameters such as mutation probability, population size, initial seed is also observed separately. They tested the effectiveness of solution on two models i.e. a layer cake model and a highly heterogeneous one. It was observed from the results that the ideal mutation rate should vary with the generation. They found that the random seeds are susceptible contrary to the use of elitism that showed much progress. From the study of population size, they came to know that the number of variables is proportional to the appropriate population size. By using large populations, more difficulty was found in finding the solution due to the evaluation of poor quality chromosomes. Also, the issues of absolute convergence and stability of optimization algorithms were observed in this study.

Yeten (2002) studied the use of genetic algorithm to improve well type, location and a track for nonconventional (nonstandard) wells. Besides, the upgradation of well controls were achieved with the help of tool built on a nonlinear conjugate gradient algorithm. The optimization were accelerated using supporting functions such as ANN and the Hill Climber (HC). Along with this, wellbore upscaling were performed by calculating skin factor which account for fine scale heterogeneity present near wellbore for each well portion. The outcomes were presented on fluvial and layered synthetic models along with a section model of a Saudi Arabian field. The uncertainty in the results of optimization process were studied with experiment design method introduced in this study.

Rigot (2003) extended the optimization engine developed by Yeten et al. (2002) by implementing an iterative approach to improve the efficiency of multilateral well placement optimization. He divided the original problem into several single well optimizations to speed-up the optimization process and improves results. He also applied a proxy to avoid running numerical simulation if the expected productivity of a certain well was within the range of validity of the proxy.

Badru et al. (2003) carried out the research to find out the applicability of the quality map concept to determine the most favorable well locations .With the help of the quality map complicated and divergent parameters leading fluid flow through porous media is simplified in to a simple 2D reservoir representation. Two approaches are there to be presented: one is the Basic Quality Map (BQM) and other is the Modified Quality Map (MQM). As compared to other optimization methods, the BQM approach does not need any simulation run once the quality map is in place. Inverse distance weighting method is utilized to give the fitness function for any given well configuration. However, the study found that the concept of quality map can be used in an optimization method as a screening tool that utilizes the numerical simulator as the correct fitness function attached with a decline (deteriorate) proxy .The quality map offered the screening of all feasible well locations through which the significant decline in the simulation runs was achieved and the use of the decline proxy leads to incredible CPU time savage.

Cruz et al. (2004) presented the study which focus on the reservoir response in 2D representation named quality map. They proposed the quality maps as the useful key for the selection of well locations, with smaller number of full field simulation runs.

Ozdogan and Horne (2006) studied the relationship between time-dependent information and its effect on decreased uncertainty and improved economic value. The researchers utilized a HGA as the optimization method, and a utility framework to find out best possible decisions for different risk attitudes. Their procedure integrated time-dependent production history as the wells are drilled into the placement decisions, leading not only to improvising upcoming drilling together with prior information, but also to optimum oil production .The research established several conclusions giving proof to the advantages of utilizing their methodology.

Onwunalu and Aziz (2006) applied a statistical proxy based on cluster analysis into the GA optimization process for nonconventional wells. His work also used Yeten's multilateral well model. The objective of applying the proxy is to reduce the excessive computational requirements when optimizing under geological uncertainty. The method is similar to the ANN method in terms of building a database of simulation results. The data base is then partitioned in clusters containing similar objects. The objective function of a new scenario can be approximated by assigning it to one of the constructed clusters. Additionally, his work extended the proxy to perform optimization of multiple nonconventional well opened at different times. When simple wells were optimized the proxy provided a close match to the full optimization by simulation only 10% of the cases. This percentage increased to 50% when multiple nonconventional wells were optimized.

Bangerth et al. (2006) discussed the different optimization algorithms (simultaneous perturbation stochastic approximation (SPSA), finite difference gradient (FDG), and very fast simulated annealing (VFSA) algorithms) efficiency, effectiveness, and reliability in the well placement problem. Moreover, the convergence properties of optimization algorithms were studied in some of the comparisons they presented two common algorithm: the Nelder–Mead (N–M) simplex algorithm and genetic algorithms (GA). The three key performance indicators were practiced: (1) Efficiency (time to obtained the optimal solution with minimum number of function evaluations; (2) Effectiveness (the algorithm value on average close to the global true solution); (3) Reliability of the algorithms, measured by the number of successes in finding the global minimum, or at least approaching it sufficiently close. For single well placement, SPSA algorithm is very effective to locate optimal solutions. It was observed that with more number of function evaluation VFSA performed better solutions than SPSA. For multiple well placements, they stated that both (SPSA and VFSA) algorithms achieved significantly well than the FDG algorithm. The results of seven wells in evaluations of few functions showed that SPSA was more effective in finding position while VFSA uses more function evaluations.

Handels et al. (2007) presented well placement optimization based on gradient-based algorithm which represent the objective function in a functional form. They then calculated the gradient of this function and used a steepest ascent direction to guide the search. For the examples they considered, these methods seemed promising due to their efficiency in terms of simulation runs. The techniques were only applied to vertical wells and they expected more difficulty in applying them to problems with arbitrary well trajectories in complex grid model. Other issues with these techniques is the incoherence in the objective function and convergence to local optima.

Chen et al. (2008) studied the use of continuous approximation to the original discrete-parameter in which the gradients can be evaluated on the approximate problem, and the optimal well location can be tracked with the use of gradient-based algorithms. A continuous functional relationship is established between the objective function and continuous parameters in spatial domain that was replaced with discrete parameters. Continuous functions can be formulated by changing discontinuous direct delta function (wells as point source) with the partial differential equation (PDE). The original wells can be represented as pseudo wells with the help of continuous function in the mass balance equation in the form of PDE. The representation in continuous functional relationship leads to calculate adjoint and standard gradient-based optimizations algorithms can be used to attain the optimum well locations.

Farshi et al. (2008) converted a well placement and design optimization framework that was developed by Yeten et al. (2002) from bGa to a real-valued continuous Genetic Algorithm (cGA). He found that the cGA provides better results when compared to the performance of bGA on the same synthetic models. Moreover, he implemented several improvements to the optimization process like imposing minimum distance between the wells and modeling curved wellbores.

Ding (2008) studied the well placement optimization using evolutionary algorithms. In well placement optimization, a large number of parameters are involved and high reservoir heterogeneities construct a non-linearity needed stochastic methods such as evolutionary algorithms, for example CMAES (Covariance Matrix Adaptation – Evolution Strategy), has been considered as one of the finest stochastic optimization technique for non-linear problem. CMAES is an alternative approach for the well placement, and it gives comparable results with respect to the genetic algorithm. But CMAES can provide more accurate and better solution. However, the population size in CMAES has an impact on the optimization results for well placement. The efficiencies of both genetic algorithm and

CMAES depend also on model parameters, such as discretization steps in the genetic algorithm, the step size or the learning rate in CMAES. Determining best model parameters for well placement is a key issue to improve the accuracy and effectiveness of evolutionary algorithms.

Nakajima and Schiozer (2009) offered procedure for the well and placement optimization by using two stages of optimization. After this, they performed searching in each sector for the best location of a single well. Proceeding to the next stage worked for the optimum well number by sequential exclusion of wells that obtained from the previous stage. After attainment of new number of wells, the first stage process is performed again until no observation of improvement in the objective function is recorded. The optimization were tested on heterogeneous model using light oil showed efficiency. They studied separately about the optimization of vertical and horizontal wells. The results from this study showed that the given modularization of the problem accelerates the optimization.

Emerick et al. (2009) carried out the research to optimize the well number, trajectory and location of both injector and producer wells. They implemented some constraint in the optimization process such as grid size, least distance between wells, inactive cells, greatest number of wells and user-define areas along with non-uniform shape where the optimization routine is not considered to put the well. They put forward a procedure through forming a reference population with entirely sufficient solutions to control unfeasible solutions. In the optimization process, any unfeasible solution was fixed by applying crossover between it and an individual from the reference population until the latest solution was attained. They used two different approaches to apply the method that is based on real cases of full-field reservoir models. In the first strategy, randomly defining the complete initial population and in second one an engineer's proposal comprised in the initial population. Observation showed that second strategy had concluded better results and the solutions for tested case were more intuitive. They proposed and examined an alternative optimization strategy by optimizing well type and number of an engineer's proposal. Although the final conclusions were not performed well in full optimization case. However they concluded that it can be used when there is constraints of time to carry out the complete optimization in complex models.

Gibbs (2010) conducted a study to optimize the placement of horizontal well in a gas reservoir, use of genetic algorithm reduced simulation runs in horizontal well placement. The algorithm performance was examined by five different cases, one case with a vertical well while other four having horizontal wells. The process were tested to observe the effect of placement of well in anisotropic and heterogeneous reservoirs on recovery. The wells were constrained by surface gas rate and bottom-hole pressure for all examples.

Onwunalu (2010) developed new procedures for well placement optimization using particle swarm optimization (PSO) as the underlying optimization algorithm. In order to treat large-scale optimizations involving significant numbers of wells, established a new procedure, called well pattern optimization (WPO). WPO avoids some of the difficulties of standard approaches by considering repeated well patterns and then optimizing the parameters associated with the well pattern type and geometry. Also, the application of a metaoptimization procedure is applied which optimizes the parameters of the PSO algorithm during the optimization runs. Metaoptimization comprises the use of two optimization algorithms, where the first algorithm optimizes the PSO parameters and the second algorithm uses the parameters in well placement optimizations.

Wang et al. (2011) applied retrospective optimization (RO) to study well placement problem under uncertainty. The main feature of RO is that it doesn't consider all realizations in optimization algorithm of all iterations. Though, RO outlines a sequence of approximate sub problems for optimization, which sequentially treats the growing numbers of geological realizations. They introduced *k*-means clustering for choosing realizations. The performance of RO procedure were tested on three examples presented. They used particle swarm optimization and simplex linear interpolation based line search as the core optimizers. Their results demonstrated the benefits of the RO procedure relative to exhaustive sampling and, within the RO procedure, the advantage of cluster sampling relative to random sampling. They obtained same optimum solution using RO as given by an exhaustive optimization approach, while RO requires fewer simulations. The result highlighted the suitability of cluster-based RO for large numbers of geological realizations.

Taware et al. (2012) offered a procedure for optimization of well placement to find the potential areas of undrained oil and this method for optimization depends on streamlines and total time of flight. In this procedure utilization of the dynamic measure based on the combination of static and dynamic factors with the total streamlines time of flight to recognize "sweet spots" of infill drilling. The major benefits of this approach is the calculation of dynamic measure map with computational efficiency. Due to its efficiency this method is appropriate for large-scale field application under uncertainty assessment by examining the numerous geologic realization. The infill places seem to be uniform along with the performance of infill wells in the field when it is based on dynamic measure map.

Bouzarkoun et al. (2012) investigated well placement optimization under geological uncertainty. They proposed approach uses already simulated well configurations in the neighborhood of each well configuration for the objective function evaluation. Their defined methodology can be incorporated with any algorithm of optimization; they combined it with CMA-ES algorithm. For each well configuration this approach used all the possible realizations in comparison to the reference approach. It is shown that the proposed approach is able to reduce significantly the number of reservoir simulations by more than 80% for the reservoir case in this study.

Bellout et al. (2012) offered a joint methodology to optimize well placement and well control in the optimization problem, instead of sequential process. In this approach, the two different optimizations are considered in a nested fashion. The outer loop involves a well location optimization, while the inner loop is based on optimizing well controls for fixed well positioning. In their founding, joint optimization yields a significant increase, of up to 20% in net present value, when compared to reasonable sequential approaches. As compared to the sequential method, this approach yet require large number of objective function evaluations.

Li and Jafarpour (2012) the well placement and control optimization problem was solved in two steps. First, solved the well placement with gradient free optimization along with the function of well spacing constraint then they use gradient based method for well control optimization. They introduce a well-distance constraint into the well placement objective function to avoid solutions containing well clusters in a small region, the problem was solved using penalty method.

Isebor (2013) implemented and build up new methods for the generalized field development optimization problem and also gave a general framework to deal with the problems of MINLP including categorical, continuous variables and integers. MADS, PSO and a PSO-MADS hybrids are different approaches that will be applied and compared with Branch and Bound (B&B), traditional MINLP method to utilize in our framework as the optimization engine. Some common barriers handling tactics will be included in the framework. For well control optimization problems they additionally emphasize the competence of the novel PSO and PSO-MADS filter based limitations handling methods. Dealing with the complete development problems of petroleum field, and a true MINLP problems, they also optimized the well locations and control, number of wells, the well types along with their drilling schedule. Moreover, for this problem they also compared the performance of different algorithms incorporating B&B algorithm.

Awotunde and Sibaweihi (2014) suggested the use of multi objective optimization by incorporating NPV and VRR to solve well placement optimization problem. They carried out their research in three stages via using NPV, VRR and weighted sum of the NPV and the VRR respectively as objective functions. To illustrate the relative significance of the NPV and the VRR in the third stage they utilized a collection of four weights and also made comparison of how these weights influence the optimized NPV and VRR values is given. They used two evolutionary type algorithms to solve the optimization problems, one is the Differential Evolution (DE) and second is Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES).

Awotunde (2014) proposed the method to solve the well placement optimization problem constrained to any desired minimum well spacing (the minimum distance between any two wells that a company or an asset team considers technically safe). The circular approach is used to solve the problem. Two examples were tested to show the effectiveness of the method.

Awotunde (2014) presented the Joint Optimization of Well Placement and Control. The methodology proposed how to effectively optimize well placement and rates without dramatically increasing the size of the optimization problem. In the first part, two approaches (Polynomial and Trigonometric) were presented to reduce the number of design variable. In the second part, with the help of well control variables, the optimal number of wells and well type were optimized.

Shirangi and Durlofsky (2015) studied the closed loop optimization of well placement under uncertainty using sample validation process. They proposed a methodology for field development optimization along with the geologic uncertainty present in the model. The process involves three phases: optimize field development plan on current geologic knowledge; obtaining new information from drilling and production of new wells; updating models with new information. In the process, they optimize well number, type, location and controls of new wells with the help of hybrid particle swarm optimization. As a part of closed loop optimization process history matching is performed with adjoined gradient-based method, because matching process is fast as compared to optimization, they generated multiple history match realizations after than optimization is performed on the representative set of realizations. They introduced a procedure for optimization with sample validation (OSV), in which number of realization increases if pertinent validation criteria is not satisfied.

Most of the research carried out on well placement optimization focused on the optimization algorithms performance and some helper methods which try to reduce the computational time by using proxies and some also studied how to deal with geological uncertainty in well placement problems. These studies showed the importance of well placement optimization in field developments.

2.2 Review of Literature on SAGD

Different researchers investigated different aspects of theoretical, experimental and numerical studies of SAGD process. The process of gravity drainage was first originated by Butler (1970). At the same time the progression in the horizontal well technology made it possible to test in heavy oil application.

Butler et al. (1981) developed the concept of steam assisted gravity drainage (SAGD) for heavy oil reservoir. The process involved horizontal pairs of wells in which the top one act as injector to inject steam while the other act as producer, the gravity plays important role in the flow of fluid to the production well.

Butler et al. (1994) illustrated the dome-shaped structure to present concept of steam chamber along with the projection of steam fingers from its upper surface. With the help of these fingers steam flows and condenses on the surface and that heats up the oil which is present at the surrounding of the fingers. The heated oil flows in the downward direction around the perimeter that is present into the steam chamber and strolls in counter-current flow in opposition to the steam.

Kisman and Yeung (1995) concluded from the study of numerical simulation that the lower the operating pressure tends to produce the lower oil rate resulted in low SOR. They conducted the reservoir simulation sensitivity studies in the Burnt Lake oil sands lease to observe the relation.

Farouq Ali (1997) studied the effect of geology of the formation presents and how it is important in SAGD field applications. The performance of SAGD procedure is influenced by Shale barriers and other geological that are depicted in heterogeneous reservoirs (Richardson et al. 1978), these characteristics of heterogeneity plays a significant role in the propagation of steam. As, high permeability zones are often channel selectively for steam floods due to its better mobility as compared with oil and water. Also , due to the usage of long horizontal injector, the injectivity variance along the well caused by the local heterogeneity makes it challenging to build up an even injection profile. From the results, it was concluded that the steam chamber forms only in the region of well segments surrounded by high permeability formation.

Ito and Suzuki (1999) conducted the study of the SAGD field application with the help of numerical simulation. They performances of the SAGD project in terms of recovery were calculated for the Hangingstone oil sands reservoir. They examined recovery mechanisms and the optimization of sub-cooling temperature and the results obtained presented the optimum sub cool of approximately among the range of 30 and 40°C.

Nasr et al. (2000) conducted the study the countercurrent and cocurrent flows in a non-steady state of steam flow with different permeabilities and initial gas saturations. They used the laboratory steam-front dynamic tracking technique and a CMG STARS numerical model. They applied two-dimensional scaled gravity drainage experiments to characterize the process of SAGD for heavy oil/bitumen reservoirs. During the research they prepared visual inspection of the growth of steam chamber and compared with numerical model predictions. They examined the countercurrent and cocurrent relative permeability curves of the steam-water that demonstrate the major difference. Due to the consequences of viscous coupling of different phases they attributed it to the differences in the concurrent and countercurrent relative permeabilities.

Tan et al. (2000) studied the significance of utilizing a discretized wellbore model for SAGD simulation and they discovered that discretized well model is crucial for production of SAGD well pairs and saturation profiles for start-up and for predicting the temperature accurately.

Egermann (2001) implemented reservoir simulation techniques to demonstrate that the rate of injection should be controlled so that the chamber is as large as possible without any live steam production. In Saskatchewan, the model was trained to Mobil's Celtic SAGD pilot and presented that the operating approach concluded in a large inventory of heated oil and then condensation was done in the chamber of depletion. This inferred that a large amount of injected energy was transmitted directly towards the hot fluid pond presenting in the chamber instead of the oil sand at the edge of the chamber.

Queipo et al. (2001) studied the application of surrogate models that based on Design and Analysis of Computer Experiments (DACE) model, adaptive sampling and neural networks to establish a more accurate process for the optimization of SAGD. They optimized the cost function that is a weighted sum of the cumulative injection of steam and cumulative production of oil. The inter-well bore distance, sub cool and the enthalpy and pressure of injected steam. After five years of production. They suggested that an operating strategy including cSOR equivalent around 3.8 in a reservoir along with a thickness of 54 meters.

Edmunds et al. (2001) examined the most favorable operating pressure and economics of SAGD reservoirs by using reservoir simulation. The modeled reservoir used has a thickness of 10 and 25 m and recovery of 55% of the OOIP with constant operating pressure throughout the simulation time. The results showed the economics of SAGD are more sensitive to the cSOR than the rate of oil production. Also, they examined by simulation that for typical McMurray reservoirs the most favorable stable operating pressure can be as low as 400 kPaa. Moreover, they inferred that the higher the gas price, the more crucial the cSOR’s influence on the economics of SAGD.

Gates and Chakrabarty (2005) studied the use of genetic algorithm to optimize parameters of SAGD. They performed the simulations on CMG STARS™ thermal reservoir simulator for the optimization of steam injection strategy in a generic McMurray reservoir, the yardstick used to evaluate the performance was cumulative steam oil ratio (cSOR). The high computational time required to run several hundred reservoir simulation runs for the optimization problem, limits the study to the simplified two-dimensional (2D) model. They came up with the results that the cSOR can be enhanced considerably through operating SAGD with the constant profile of steam injection pressures during the life time of simulation. They concluded that the pressure of steam injection should be comparatively high at the start when chamber contacts the overburden and lower afterwards (thus lower saturation temperature) to decrease cap rock heat losses.

Cardwt et al. (2006) presented the new technique which use both the automation of the manual approach and the optimization of the automated approach. The theme of the study was to apply the optimization approach that finds the global optimum using the defined objective function in an optimal fashion. They used cumulative SOR as a proxy for the optimization of economic objective function. The SAGD model used 3D reservoir description and has been limited to a single well pair. The use of parallel calculations and dynamic grid with an individual reservoir simulation and an automated sequence that runs multiple simulations in parallel made it possible to perform optimization of complex and detailed reservoir models. It was noted that the cSOR can be reduced by operating with a profile of steam injection pressures over the life of the SAGD process beyond that of a constant operating pressure.

Yang and Nghiem (2009) discussed the application of global optimization and presented the uncertainty present in the optimization problem. They introduced the workflow of experimental design, response surface generation and Monte Carlo simulation techniques for SAGD simulation studies, the workflow was tested on a real field case example. First, the history match of the simulation results were performed with field data, the use of experimental design and DECE (Designed Exploration and Controlled Evolution) optimization methods made it to achieve a quick and improved history match that was difficult with the traditional manual match. Second, the SAGD operations conducted in different phases uses the rate of steam injection and the producer liquid withdrawal rate which were adjusted for the optimization of SAGD performance. In the end, a polynomial response surface was built by applying the method of response surface generation and experimental design through which the net present value (NPV) of the SAGD project is correlated with uncertain parameters and a SAGD design parameter. The uncertainty of SAGD forecasts were quantified using Monte Carlo which uses the cumulative probability distribution of the NPV at different values of the SAGD design parameter. It was concluded that with the help of optimization the economics of this project are enhanced significantly

Mojarab (2011) discussed the application of a new well configuration to SAGD processes in Athabasca and Cold Lake reservoirs. The wellbore model was coupled with fully implicit thermal-reservoir simulator, CMG's STARS 2007, 3D simulation model was created to observe the effect of frictional pressure drop and heat losses along the wellbore. They conducted sensitivity analyses to optimize the injection pressure. Once the injection pressure were optimized, the study of new well configurations was performed on these models. This work presents the conclusion in the way that the SAGD process performance can be considerably enhanced in the reservoirs of Athabasca and Cold Lake by means of varying the well configuration.

Tamer and Gates (2012) discussed the performance of steam-based gravity-drainage processes in a heterogeneous reservoir. The effect of position and geometry of steam injectors were examined. With the use of detailed, 3D, geo-statistically populated, and large-scale thermal reservoir-simulation model derived from core-data examinations of the Dover pilot site the effect of different injection-well configurations that are single horizontal (typical SAGD), offset SAGD, and vertical/horizontal well combinations have been assessed. The analysis shows that how energy delivers to the reservoir was impacted by injection well-configuration, how thermal efficiency affected and how it modifies the evolution of the steam-conformance zone and oil-flow dynamics in the reservoir. The results concluded that in some cases the steam can be delivered more efficiently through several vertical injectors than a single horizontal injector.

2.2.1 Heat Transfer Mechanism of SAGD Process

It is commonly believed that conduction is the dominant heat-transfer mechanism at the edge of the chamber. Heat transfer by convection is not considered in classic SAGD mathematical models such as the one derived by Butler. Researchers such as Butler and Stephens (1981), Reis (1992), Akin (2005), Liang (2005), Nukhaev et al. (2006), and Azad and Chalaturnyk (2010) considered the conduction from steam to cold reservoir to be the only heat-transfer component. Farouq-Ali (1997), Edmunds (1999a, b), Ito and Suzuki (1996, 1999), Ito et al. (1998), Sharma and Gates (2011), and Irani and Ghannadi (2013) questioned the assumption that thermal conduction dominates heat transfer at the edge of a SAGD chamber. Sharma and Gates (2011) and Irani and Ghannadi (2013) studied convective flux from condensate flow at the edge of an SAGD steam chamber. Irani and Ghannadi (2013) derived a new formulation that solves the energy balance and pressure-driven condensate flow normal to the steam-chamber interface into the cold bitumen reservoir and concluded that the assumption of conduction-dominated heat transfer is valid; however, all previous analyses do not include convective heat transfer arising from draining bitumen and condensate. Although a few researchers have studied convective flux from condensate flow at the edge of an SAGD steam chamber (e.g., Sharma and Gates 2011; Irani and Ghannadi 2013), there is a lack of understanding of bitumen and condensate drainage parallel to the edge of the chamber and of its effect on transverse heat transfer into the oil sand beyond the chamber.

2.3 Review of Literature on VAPEX

Most of the work that have been carried out in VAPEX focused on the experimental side of the process with few researchers studied the simulation and optimization of the method.

Allen (1970) introduced the concept of Vapex process in which hydrocarbon solvent were injected as an alternative of steam in cyclic steam stimulation (Allen 1970; Allen 1976). He further studied the use of blend gaseous phase, in which carrier gas is mix with solvent as an injection fluid (Allen 1977).

Butler and Mokrys (1989) modified the idea by injecting solvent with analogous well configuration as SAGD and observe the effect of gravity drainage in the process. Since then the process were given named as VAPEX and has been the prime focus of researchers. In this process, the solvent is injected via top horizontal well act as injector while the oil is produced from the bottom horizontal well placed parallel to injector well. The injected solvent drive the oil by reducing oil viscosity at the solvent oil interface with the help of vapor diffusion and dilution which further favored by gravity.

Butler and Mokrys (1989, 1991) use the experimental setup of vertical Hele-Shaw cell with different solvents to examine the different aspects of Vapex process. They conclude that the actual representation of pore scale phenomenon was not be seen in Hele-Shaw cell, to mimic typical porous media sand pack models can be used. Many investigators discussed different geometries of cylindrical and rectangular sand pack models which uses different sizes of glass beads or sand with different permeability to simulate the porous media with different permeability. The sand packed model experiments were carried out by these authors; Mokrys and Butler (1993), Das and Butler (1994), Jiang and Butler (1996), Jiang

(1997), Butler and Mokrys (1998), Jin (1999), Butler and Jiang (2000), Oduntan et al., (2001), Karmaker and Maini (2003), Yazdani and Maini (2004), and El-Haj (2007). The results showed that the porous media process performed ten times faster than predicted on Hele-Shaw cell experiment.

Jiang (1996) discussed the effect of heterogeneity on different heavy oil reservoirs with the use of both homogenous and heterogeneous reservoir packed models, propane and butane were characterized as solvent. Also, the performance of vapex process were observed with different well configuration, well spacing, temperature, permeability, viscosity of heavy oil, and solvent injection rates. The results concluded the effect of heterogeneity is more significant in case of low-permeability layer or shale presence.

Butler and Mokrys (1998) studied the performance of vapex process in presences of bottom aquifer on Peace River bitumen and Lloydminster heavy oil with propane as solvent. Experiments showed an active aquifer underlying an oil zone makes the reservoir more valuable because of the opportunity it offers for spreading a hydrocarbon vapor solvent directly with the oil formation increasing vapor oil contact widely and enhanced the performance of process.

Butler and Jiang (2000) examined the effect of well configuration and spacing experimentally and its influence on the performance of the process. The main observation indicates that with the wider lateral spacing higher production rates were achieved but with the compromise of communication time between injection and production well.

Nghiem et al. (2000) studied the compositional simulation of vapex process with asphaltene precipitation options. They modeled the vapex process with Athabasca heavy oil with the injection of propane as a solvent. The results of the simulation concluded that the process of deasphalting can reduce the viscosity of oil which favors enhanced production rate. But, the effect of asphalting precipitation may plug the formation pores which results in permeability reduction.

Frauenfeld et al. (2004) discussed the experimental evaluation of solvent-assisted process for bottom-water reservoirs and they found there were no significant precipitation and upgrading. Though, it could be probable to initiate asphaltene precipitation with the increasing solvent loading.

Rahnema et al. (2007) examined the role of gas cap in vapex process with different well configuration and lateral spacing. The experimental data used to develop a numerical simulation model as a two dimensional sand-packed reservoir. It was found that optimal well location obtained for injection well at oil and gas contact. Furthermore, the result presented that lateral spacing has a negligible effect on recovery.

Moghadam et al. (2007) investigated the variation in permeability and how it affects the vapex performance with pure propane as injection fluid. The authors concluded that oil production rate is dependent on the square root of permeability for permeability value close to 100 Darcies.

Haghighat and Maini (2008) examined the effect of asphaltene precipitation experimentally in Vapex process and the pros and cons of precipitation were discussed. It was observed that at higher injection pressure the oil produced was significantly upgraded. They showed that the oil produced at higher injection pressures was significantly upgraded however the reduction in viscosity by asphaltene precipitation did not lead to higher production rates. Moreover, the reduction in viscosity was nullify by the associated damage to formation permeability.

Zeng et al. (2008) studied a new tee shape well pattern to see the performance of vapex process, it was found that with this configuration the rate were enhance by two to ten times over the typical method. In this study, they proposed an additional horizontal well act as injector perpendicular to the producer and the injector in conventional configuration, the additional well diluted the heavy oil as a result of solvent injection in both axial planes.

Alkindi et al. (2010) investigated the importance of reservoir height on the drainage rates in a Vapex process. It was observed on the standard analytical model of Butler-Mokrys that the drainage rates has higher than square root dependency on reservoir thickness.

Muhamad and Upreti (2012) studied the optimal control of vapor extraction process of heavy oil experimentally. The presented solvent injection pressure versus time as a control function to enhance the oil production rate. The experiment were design based on mass transfer model to perform this work. Different experiments were performed to validate the accuracy of process. The results conclude that oil rates predicted with optimal control algorithm is in agreement with the solvent injection pressure policy.

Haghighat and Maini (2013) explained the effect of temperature on the vapex performance. The experiments were performed in a large high pressure physical model which was preheated to three different temperature values and propane was used as injection fluid. At high temperatures, higher rates was obtained in the early time of production without increasing injection pressure. Furthermore, the increasing injection pressure along with higher temperature further enhanced the process.

2.3.1 Optimization and Optimal Control

An optimal control is a function that optimizes the performance of a system changing with time, space, or any other independent variable (Upreti, 2012). Optimal Control is the optimization of an objective function subject to the equations in a system, with some constraints. It is equivalent to multi-parameter optimization. With large number of parameters available to optimize in general, optimal control unleashes an infinite search space to find optimal solutions else unfeasible with traditional optimization (Upreti, 2012). The literature showed most of the work has been conducted to understand the transport mechanism and parameters affecting the performance of process. Researchers focused to examine the effect of important parameters such as solvent injection pressure, injection rates, oil viscosity, and oil production rates, no one has performed the stochastic optimization of control parameters with numerical simulation.

CHAPTER 3

STATEMENT OF THE PROBLEM

3.1 Research Gap

As mentioned in the previous section, well placement is one of the vital assignments in field development planning; proper well placement can considerably enhance the economic value and the reservoir performance of the field. Drilling horizontal wells requires large capital investment and if errors are made during the selection process it is even more costly to correct them. Horizontal well location and orientation optimization involves estimating the optimum well heel and toe locations. Several constraints need to be considered in the optimization process in order to make the solution realistic and achievable. Constraints such as minimum and maximum bounds are simple but some highly nonlinear ones like avoidance of well collisions with each other require cautious handling.

The use of well spacing constraint in horizontal wells has not been considered in well placement optimization in any of the current literature. Moreover, the application of well placement optimization has not been discussed in heavy oil recovery process of SAGD and VAPEX. This dissertation emphasis on the development of efficient well spacing constraint optimization and its application for heavy oil field development optimizations. The main focus of this study is the enforcement of minimum horizontal well spacing constraints in SAGD and VAPEX processes. We applied Particle Swarm Optimization (PSO) algorithm to different problem to test the effectiveness of solution. The concept of minimum horizontal well spacing applied by defining an ellipse around the well such that it acts as the drainage area and no other well can come close to it.

3.2 Research Objectives

The main objectives of this research are to study

- To enforce the minimum horizontal well spacing constraints in WPO of SAGD and VAPEX processes.
- To optimize injection and production rates in SAGD and VAPEX.
- To optimize the vertical distance between injector and producer.
- To compare the performance of joint solution of the well placement and control optimization problem.

The outcomes of this research should answer the following concerns:

- How much is the difference between the results when using different cases as evaluation
- The variation of the results on multiple realizations for different scenarios.

CHAPTER 4

THEORETICAL BACKGROUND AND OPTIMIZATION

This section provides some understandings on the topics related to this study.

4.1 Optimization Practice

Optimization is a process of finding and comparing feasible solutions until no better solution can be found. The optimization process requires thousands of function evaluation and in case of well placement thousands of reservoir simulation runs that means computational costs and as the computational capabilities of the computers are increasing using optimization methods in well placement becomes more and more feasible. Figure 5 displays a schematic illustration of a process or objective function to be optimized.

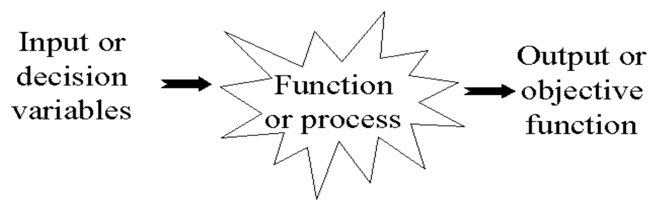


Figure 5: Optimization Process Flow

The decision variables in well placement and control optimization problem are locations, length of horizontal section, orientation, and rarely injection and production rates. Any optimization has the main objective of obtaining the highest or lowest global value of an objective function. Any criterion including the net present value (NPV), recovery factor (RF), or cumulative oil production from the field can be considered.

The optimization techniques can be broadly categorized as gradient based optimization and stochastic optimization. Gradient based optimization starts from initial guess and moving in the direction of increasing or decreasing gradient and is highly dependent on initial values. On the other hand, the stochastic optimization is randomly move over the search space and depends on the surface of the objective function and size of the search space. It is more appropriate to apply stochastic search algorithm in order to avoid it getting trapped into the numerous local optima.

Stochastic optimization algorithms, are considered to be more effective in finding optimal solutions of nonsmooth or nonconvex or multi modal problems. These algorithms approach do not require the computation of derivatives and have a higher likelihood of finding the optimum solution in complex problem. The global algorithms have the ability to move randomly from one region of the problem space to another and hence tend to cover a broader surface in their search for optimal solutions. However, a major limitation of such algorithms is the computational expense incurred in running them. The PSO algorithm belongs to the stochastic family used in this study as optimizers.

The population size (N_p) is calculated with given relation for both algorithms,

$$N_p = 4 + floor\left[3 \times \log(D)\right] \tag{1}$$

Where D is the design variables or problem dimension (i.e. number of variables to be optimized) and floor ( ) is a function that map a number to its nearest integer towards minus infinity. This relation is widely used in literature (Liao and Stutzle, 2013) and (Auger and Hansen, 2009) to evaluate population size in evolutionary strategies.

4.1.1 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a robust stochastic optimization technique based on the movement of swarms (Eberhart and Kennedy 1995). The PSO algorithm has been implemented successfully in several applications like geophysical inverse problems, dynamic economic dispatch problem, water reservoir operations and planning, pole shape optimization, placement of sensors for civil structure. This evolutionary technique was motivated by the behavior of organisms such as fish schooling and bird flocking combines social psychology principles in socio-cognition human agents and evolutionary computations. PSO technique conducts search for optimum solution using a population (swarm) of particles (individuals) that are represented as $\vec{x}_j \in \mathbb{R}^D$. In a PSO system, particles change their positions by flying around in a multi-dimensional search space until a relatively unchanging position has been encountered, or until computational limitations are exceeded. PSO system a social-only model and a cognition-only model. The social-only component suggests that individuals ignore their own experience and adjust their behavior according to the successful beliefs of individuals in the neighborhood. On the other hand, the cognition-only component treats individuals as isolated beings. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities which leads to overcome the premature convergence problem and enhances the search capability.

In PSO algorithm, the population has N_p particles that represent candidate solutions particles are randomly generated within a predetermined lower and upper bounds and subsequent particle positions are not allowed to all outside these bounds. Each particle $\vec{x}_j$, is a D-dimensional real-valued vector and assigned a random velocity $\left(\vec{v}_j^{\,t}\right)$, maintains a memory of its previous best position $\left(\vec{x}_{pj}\right)$ with the best fitness in the neighborhood is designated as $\left(\vec{x}_g\right)$. Evaluate each particle's position according to the objective function $\left(f(\Phi):\mathbb{R}^D \to \mathbb{R}\right)$ and compare the particle's fitness value with its previous best $\left(\vec{x}_{pj}\right)$, if a particle's current position is better than its previous best position, update it as.

$$\vec{x}_{pj}^{\,(t+1)} = \left\langle \begin{matrix} \vec{x}_{pj}^{\,t}, f(\vec{x}_j^{\,t+1}) \geq f(\vec{x}_{pj}^{\,t}) \\ \vec{x}_j^{\,t+1}, f(\vec{x}_j^{\,t+1}) < f(\vec{x}_{pj}^{\,t}) \end{matrix} \right. \quad (2)$$

Update the global best fitness value corresponding best position $\left(\vec{x}_g\right)$. Update particles' velocities according to

$$\vec{v}_j^{\,(t+1)} = \omega \vec{v}_j^{\,t} + c_1 r_1 (\vec{x}_{pj}^{\,t} - \vec{x}_j^{\,t}) + c_2 r_2 (\vec{x}_g^{\,t} - \vec{x}_j^{\,t}) \quad (3)$$

Where, ω is the inertial factor that maintains a balance between the local exploitation and the global exploration abilities of the PSO algorithm, c_1 and c_2 are the cognitive and social parameters that control the extent to which particles are drawn to their 'personal best' and the swarm's 'global best' positions respectively. Whereas, r_1 and r_2 are uniformly generated random numbers. Also, move particles to their new positions according to

$$\vec{x}_j^{\,(t+1)} = \vec{x}_j^{\,t} + \vec{v}_j^{\,t+1} \quad (4)$$

Repeat steps until a stopping criteria is met (either the maximum number of iterations or a sufficiently good fitness value). The flow chart of the particle swarm optimization can be seen in Figure 6.

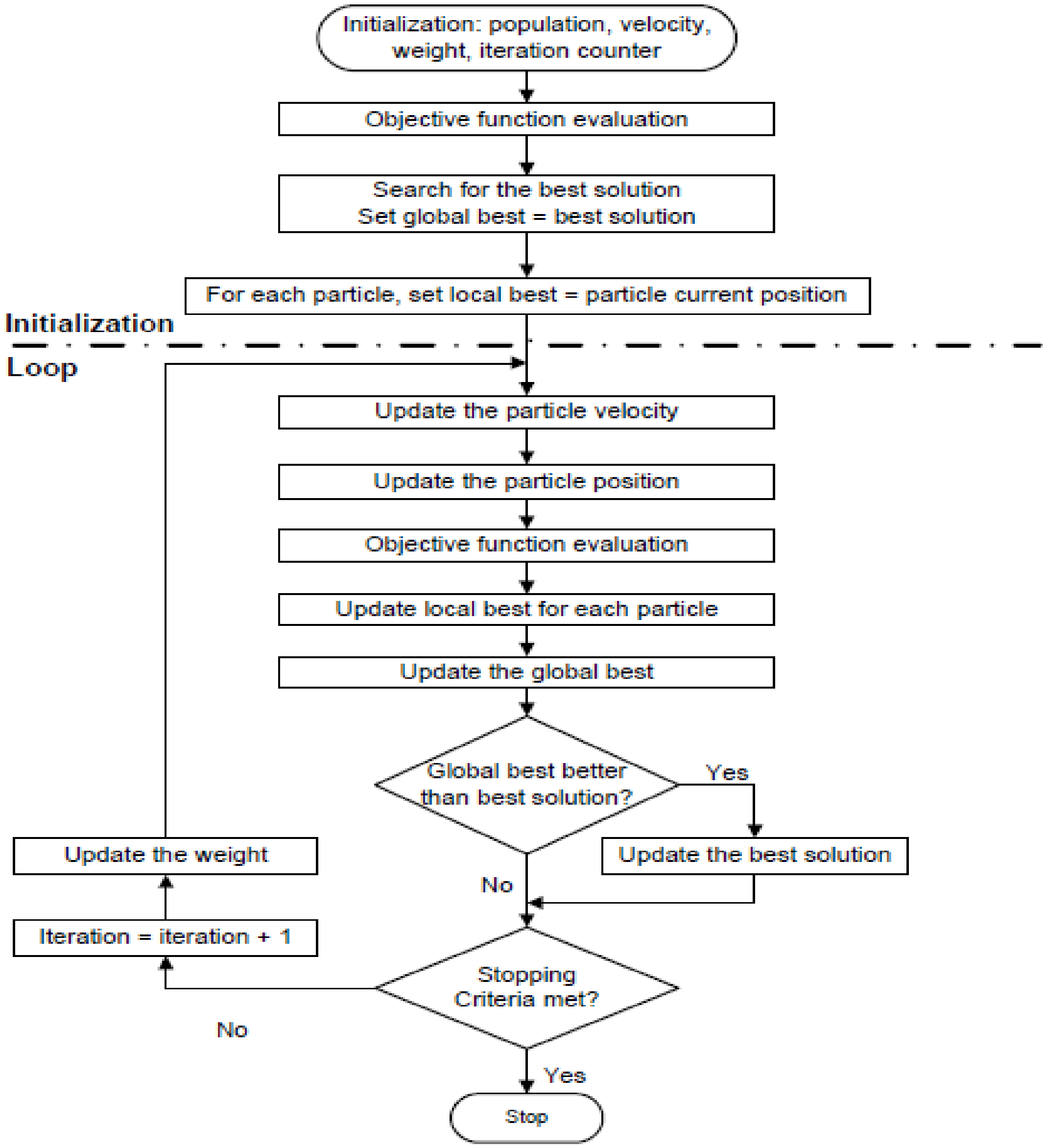


Figure 6: PSO flow chart

Like other algorithms, the PSO performance is also depends on the assigned values of the parameters in the algorithm. In this work, the value of c_1 and c_2 was set to 1.494 and the weight (ω) parameter was chosen to be 0.729, these parameter values were recommended by Clerc which were shown to perform well for these problems (Isebor 2014).

4.2 Objective Function

Objective functions (fitness, cost, error function) are performance measures that indicate the quality of different alternatives, thereby guiding an optimization algorithm towards finding the optimal solution(s) to a problem. In most well placement optimization problem, cost function is represented by net present value (NPV) to evaluate the performance of a candidate solution. To assess the viability of the different EOR scenarios, NPV becomes a critical yardstick and should be ranked up with the best alternatives. The thought supporting the use of NPV as an objective function is to take more consideration of the economics of the project rather than representing a single value if considering cumulative oil production or some other parameter as an objective function. It recognizes the time value of money and applies the same weightage to all future income. Each candidate solution involves performing a simulation run to estimate the NPV.

In SAGD/VAPEX project, the capital cost at the project's beginning consists of the exploration cost, the drilling and well completion cost, steam generators capital cost, water treatment capital cost, and solvent injection capital cost. The expenditure includes the cost of steam generation, steam injection, produced water treatment, solvent handling and recompression, solvent cost and operating costs including well remediation and human resources.

In an EOR project, the net present value is assessed by relationship as

$$NPV = \sum_{t=1}^{T} \frac{CF_t}{(1+r)^t} - C_{capex} \tag{5}$$

Where T represents total production time in years; r denotes as annual discount rate; C_{capex} is the capital expenditure, which combines surface facility installation and the total cost to drill and complete all of the wells; and CF_t represents the cash flow at time t. The capital expenditure (C_{capex}) is incurred at time $t=0$ and is calculated as:

$$C_{capex} = \sum_{m=1}^{N_{well}} [C_m{}^{ver} + L_m{}^{hor} C^{drill}] + C_{\text{facility}} + C_{\exp} + C_{SG/\text{SO}} \tag{6}$$

Where N_{well} is the number of wells, $C_m{}^{ver}$ is the price to drill the vertical section (from surface to the top of the reservoir) (\$), C^{drill} represents the drilling cost per foot to drill horizontal section of the reservoir (\$/ft.), $L_m{}^{hor}$ is the length of the horizontal section (ft.). Whereas, C_{facility} represents the cost of facility to process oil to the sales point. We use the approximate relation to calculate total capex used by Onwunalu. Cost of exploration well is specified by $C_{\exp}$, where $C_{SG/\text{SO}}$ represents the cost of steam generation facility in SAGD while in VAPEX it acts as a cost of solvent processing facility.

At time (t), the cash flow CF_t is given by

$$CF_t = R_t - E_t \tag{7}$$

Where E_t and R_t stand for operating expenses ($) and revenue ($), respectively, which are functions of fluid production volumes at time(t):

$$R_t = p_o Q_t^o + p_g Q_t^g \tag{8}$$

Where p_o and p_g denote the oil price ($/STB) and gas price ($/SCF), Q_t^o and Q_t^g symbolize for the total oil volume (STB) and gas volume (SCF) produced at time(t). In all cases, there is no gas production, so $Q_t^g = 0$. The total operating expense at time(t), E_t is calculated for SAGD and VAPEX processes using equation 18 and 19 respectively.

$$E_{t,sagd} = p_{wp} Q_t^{w,p} + p_{\mathrm{steaminj}} Q_t^{w,i} + p_{op} Q_t^o \tag{9}$$

$$E_{t,\mathrm{vapex}} = p_{wp} Q_t^{w,p} + p_{\mathrm{solinj}} Q_t^{\mathrm{sol},i} + p_{op} Q_t^o + p_{solrec} Q_t^{sol} \tag{10}$$

Where p_{op} is the operating cost, p_{wp} symbolizes for the costs of water production ($/STB); $p_{steaminj}$ represents steam injection costs ($/STB) whereas p_{solinj} represents the cost of solvent injection ($/STB); $Q_t^{w,p}, Q_t^{w,i}$ and Q_t^{sol} signifies the total volumes of water produced (STB), water injected (STB) and the amount of solvent produced, respectively, at time(t). The solvent injection cost and solvent recycling cost is represented by $p_{steaminj}$ and p_{solrec} respectively. In all cases, we assume p_o, p_g, p_{wp}, p_{wi} to be constant with time. The oil price and miscellaneous costs used in calculation of NPV are presented in Table 1.

Table 1: Cost Parameters

Parameters	Value	Unit
$C_{facility}$	1.00E+06	USD
C_{SG}	2.26E+06	USD
C_{SO}	100000	USD
C_m^{ver}	6.00E+05	USD
C^{drill}	600	USD/ft.
p_o	65	USD/bbl.
p_g	3	USD/MScf
p_{op}	3	USD/bbl.
p_{wp}	5	USD/bbl.
$p_{steaminj}$	8	USD/bbl.
p_{solinj}	2	USD/bbl.
p_{solrec}	0.17	USD/bbl.
r	10	%

4.3 Well Placement and Control Optimization

The purpose of this research is to implement the well spacing constraint in the well placement and optimization problem. The PSO algorithm is used to optimize this problem. This research will add an improvement to the current literature. The main understanding of the problem is achieved by outlying the main steps in the well placement and control optimization;

- Formulation of wells placement problem and coding the solution for PSO
- Generate initial population of possible solution
- Examine for boundary constraint and spacing constraints

- Evaluate the fitness of the individual particle by performing simulation and rank them
- Update the particle position, velocities and local solution
- Produce the next generation and designing velocity and position parameters

The framework for well placement optimization consists of a good model representing possible solutions. The parameters to optimize in the optimization problem obtained from the model are in the form of particle in PSO. These parameters characterize the well location and control for numerical simulation; the results of the simulation are then used to calculate the objective function. In this study, the objective functions were evaluated with GeoQuest's ECLIPSE which act as a numerical simulator. The input files for each simulation were created by a self-developed code which uses parameter from the model engine of optimizer. The next section will discuss how the modelling of horizontal wells and the constraint handling of well placement are formulated.

4.3.1 Problem Formulation

The decision variables in well placement and rate optimization problem are locations, type, and injection and production rates. In this study, the formulation defined by Farshi (2008) were used with some modification. In this work, a fully horizontal well was considered that can be placed in x-y plane of the reservoir. The trajectory of a horizontal well in three-dimensional (3D) space can be mapped as a straight line connecting two points in 3D space as shown in Figure 7. The design variables used in optimization problem to define the trajectory of the horizontal well can be characterized by five variables i.e. the three coordinates of heel $\left(x_1, y_1, z\right)$, total well length $\left(l_h\right)$, and the counterclockwise angle $\left(\theta\right)$

from the *x*-axis. Other dependent parameters that are necessary to define horizontal well such as coordinates of toe can be calculated during optimization, from the independent variables stated above according to the following equations:

$$x_2 = x_1 + \mathrm{l_h}\cos(\theta) \tag{11}$$

$$y_2 = y_1 + \mathrm{l_h}\sin(\theta) \tag{12}$$

The vector of design variables to be optimized for each well is designated by:

$$V = \left(\begin{bmatrix} x_1 \\ y_1 \\ z_1 \\ l_h \\ \theta \end{bmatrix}_n , q_n \right) \tag{13}$$

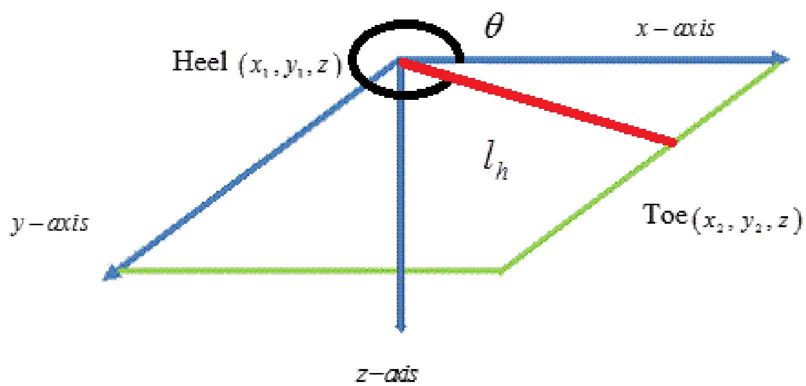


Figure 7: Representation of Horizontal well

The optimization routine should be able to handle the constraint outlined for all kinds of horizontal and vertical wells. The lower and upper bounds are defined to constrain the well location inside the reservoir boundaries. The other constraints specified; signify the maximum allowable length, or orientation in any directions of the wellbore. In some cases, the toe point calculated from the parameters $\left(x_1, y_1, z, \theta, l_h\right)$ which obtained from optimization engine fall out of the grid range. This constraint is handled outside the algorithm using repair method such as if the toe coordinates calculated fall outside the reservoir limits it is restricted within the domain of reservoir.

If the toe coordinates fall outside of the reservoir limit in either east, west, north, or south direction, the angle is randomly recalculated to limit it in the reservoir as shown in Figure 8. The red line shows horizontal well obtained from optimizer which were repaired as green line in the Figure 8. The recalculated angle is updated and sent back to the optimizer.

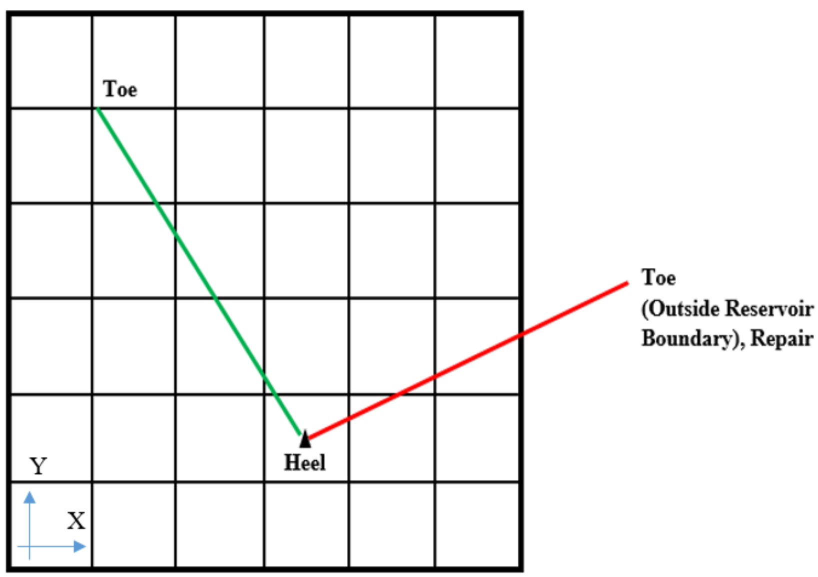


Figure 8: Repair Method Illustration for Boundary Constraint

In finite difference simulator, the well passes and completed in the center of each grids. In this problem, the horizontal well can be placed in any direction at any angle with x-axis. If the well passes the grids in x-direction or y-direction, it can easily be defined in the simulator but if the well orientation is crossing at any angle in x-y plane it requires additional input to define the representative well. It might be possible in some cases that the well passes some grids off centrally but in simulator it is defined as it passes through the center of grid. The well representation in the simulation model is shown as a staircase manner as shown in Figure 9. The mapping of the trajectory as symbolized by green line to the well trajectory defined in simulator as red line is implemented with the codes developed in this study. It can be observed that the trajectory (red lines) is larger than the actual well (green line). This problem is handled using calculation of connection factor or Well Index (WI) which was obtained using projection method (Shu, 2005).

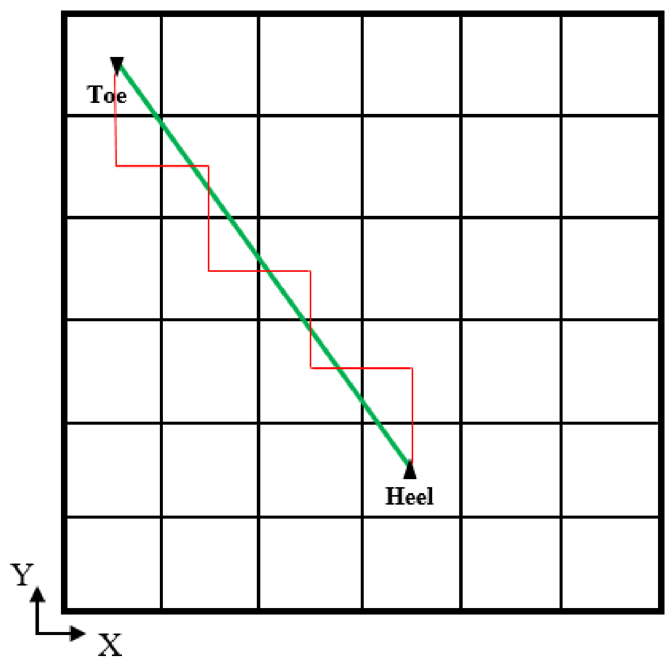


Figure 9: Definition of Staircase Well Representation in Simulation Model

The program self-developed for well index calculation use the values of heel and toe position of well and map the grids through which well passes and its entry and exit points.

4.3.1.1 Well Index Calculation

The projection WI is developed by Jonathan Homles (Schlumberger) to apply correction in non-conventional wells. It is based on a three-part Peaceman formula which takes into account the following factors:

- The orientation of the well.
- The permeability of the grid block.
- The portion of the grid block which is perforated.
- The effective wellbore diameter in each of the orthogonal X, Y and Z directions.

The well trajectory were projected onto three axis as presented in Figure 10. The equations used in the program to calculate well index are presented next.

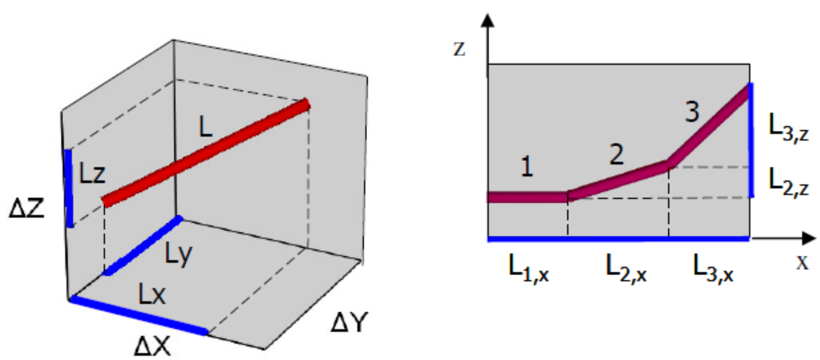


Figure 10: Well Trajectory Projected into the Axis, and Projection of Well Segments (Shu 2005)

$$WI_x = \left(\frac{2\pi\sqrt{k_y k_z} L_x}{\ln\left(\frac{r_{o,x}}{r_w}\right) + s} \right)_i \tag{14}$$

$$WI_y = \left(\frac{2\pi\sqrt{k_x k_z} L_y}{\ln\left(\frac{r_{o,\mathrm{y}}}{r_w}\right) + s} \right)_j \tag{15}$$

$$WI_z = \left(\frac{2\pi\sqrt{k_x k_y} L_z}{\ln\left(\frac{r_{\mathrm{o,z}}}{r_w}\right) + s} \right)_k \tag{16}$$

$$r_{o,x} = 0.28 \frac{\left(\left(\frac{k_y}{k_z}\right)^{1/2} \Delta z^2 + \left(\frac{k_z}{k_y}\right)^{1/2} \Delta y^2 \right)^{\frac{1}{2}}}{\left(\frac{k_y}{k_z}\right)^{1/4} + \left(\frac{k_z}{k_y}\right)^{1/4}} \tag{17}$$

$$r_{o,\mathrm{y}} = 0.28 \frac{\left(\left(\frac{k_z}{k_x}\right)^{1/2} \Delta x^2 + \left(\frac{k_x}{k_z}\right)^{1/2} \Delta z^2 \right)^{\frac{1}{2}}}{\left(\frac{k_z}{k_x}\right)^{1/4} + \left(\frac{k_x}{k_z}\right)^{1/4}} \tag{18}$$

$$r_{o,\mathrm{z}} = 0.28 \frac{\left(\left(\frac{k_y}{k_x}\right)^{1/2} \Delta x^2 + \left(\frac{k_x}{k_y}\right)^{1/2} \Delta y^2 \right)^{\frac{1}{2}}}{\left(\frac{k_y}{k_x}\right)^{1/4} + \left(\frac{k_x}{k_y}\right)^{1/4}} \tag{19}$$

$$WI^{pj} = \sqrt{WI_x^2 + WI_y^2 + WI_z^2} \tag{20}$$

Where $r_{o,\mathrm{x}}, r_{o,\mathrm{y}}, r_{o,\mathrm{z}}$ represents the Peaceman radius, $k_x, \mathrm{k}_\mathrm{y}, k_z$ symbolize the parameters for permeability in x, y and z direction, $\Delta x, \Delta y, \Delta z$ are defined as the projected length in x, y and z direction of the grid. WI^{pj} is the well index or connection factor which has to be defined in the input data of the simulator for any such wells passing the grids off centrally.

4.4 Constrained Optimization

A constrained optimization problem (COP) is the process in which an objective function is to be optimized with respect to some variables under some constraints. The goal of this technique is to minimize (or maximize) an objective (cost) function along with satisfying all the constraints present. The solution obtained with COP may not be the best one when the constraints are not present. Generally, a COP can be defined as:

$$\min f(\vec{\kappa}) \tag{21}$$

Subjected to:

$$\vec{g}(\vec{\kappa}) = 0 \tag{22}$$

$$\vec{h}(\vec{\kappa}) \leq 0 \tag{23}$$

Where $\vec{\kappa} \in \mathbb{R}^M$ the vector of problem space, $f : \mathbb{R}^M \to \mathbb{R}$ represents the objective function, whereas vector-valued functions: $\vec{g} : \mathbb{R}^M \to \mathbb{R}^I$ and $\vec{h} : \mathbb{R}^M \to \mathbb{R}^J$ defines the equality and inequality constraints respectively. M, I and J are the number of design variables, number of equality constraints and number of inequality constraints respectively. The inequality constraint is not limited since any constraint of the form $\vec{h}(\vec{\kappa}) \geq 0$ can be described as $-\vec{h}(\vec{\kappa}) \leq 0$. The solution set in the problem space that fulfill all the constraints is known as the feasible set of the solution to the COP problem and the elements of this set are known as the feasible points.

4.4.1 Constraint Formulation

The formulation for constrained optimization problem is carried out by considering the minimum well spacing in terms of the area, A in acres, surrounding a particular well within which no other well should be placed (Awotunde 2014), the safest area for circular and ellipsoidal surface can be determined from:

$$A_v = \frac{\pi r^2}{43560} \tag{24a}$$

$$A_h = \frac{\pi ab}{43560} \tag{24b}$$

Whereas A_v represents the area for a vertical well and r is the minimum radius while A_h implies the area for a horizontal well. The major axis a can be calculated with the following relation:

$$a = \frac{(l_h + 2t_l)}{2} \tag{25}$$

It was assumed that $b = 2t_l$ and $r = t_l$ whereas b denotes distance to minor axis of ellipse and t_l corresponds to tolerance between end points of the horizontal well to the vertex of ellipse. The consideration of area signifies the area that an individual well can drain while restricting interference to other wells placed in the reservoir, usually circular shape drainage area implies vertical well while the ellipsoidal drainage area corresponds to a horizontal well.

The spacing constraint for horizontal well is applied by considering an ellipse around the well and checking the points of other horizontal wells on that ellipse. The length of other horizontal well is divided into equal segments, N_s whereby the corresponding points $\left(x_{i\to Ns}, y_{i\to Ns}\right)$ are validated to the test the spacing constraint on the ellipse formed. The horizontal well spacing constraint is enforced with the help of a general ellipse equation.

$$\frac{\left(x_i - h_j\right)^2}{a^2} + \frac{\left(y_i - k_j\right)^2}{b^2} = 1 \qquad (26)$$

Where $\left(h_j, k_j\right)$ represents the mid points of horizontal well on which the ellipse is formed. Each point $\left(x_{i\to Ns}, y_{i\to Ns}\right)$ is tested on the following equation:

$$D_{hp} = \frac{\left(x_i - h_j\right)^2}{a^2} + \frac{\left(y_i - k_j\right)^2}{b^2} \qquad (27)$$

If $D_{hp} \le 1$, it means the point is lying inside the ellipse and it is considered as a violation of spacing. The segments are considered to cover full horizontal well because it may happen that the heel and toe positions are outside the ellipse but the other points are violating constraint as in the case if two wells cross each other like cross (X) shape. $Ns \ge 10$ was used in this problem to cover the full range with respect to drainage area defined. Also, one point implies as a single violation of penalty, the segments division helps to put more penalty if the wells are violating more points. The segments coordinates $x_i = 1 \to N_x, y_i = 1 \to N_y$ represent grid numbers where N_x denotes number of grids in x-direction and N_y symbolize number of grids in y-direction. Each individual well segments points are tested on the well the ellipse is formed and on the subsequent well and check the well segments of other wells till the count of number of constraints achieved.

$$\begin{cases}
\vec{h}_1(\vec{\kappa}) = \dfrac{\left(x_{1,i=1\to N_x} - h_1\right)^2}{a^2} + \dfrac{\left(y_{1,i=1\to N_y} - k_1\right)^2}{b^2} \le 1 \\
\vec{h}_2(\vec{\kappa}) = \dfrac{\left(x_{2,i=1\to N_x} - h_1\right)^2}{a^2} + \dfrac{\left(y_{2,i=1\to N_y} - k_1\right)^2}{b^2} \le 1 \\
\vec{h}_3(\vec{\kappa}) = \dfrac{\left(x_{3,i=1\to N_x} - h_2\right)^2}{a^2} + \dfrac{\left(y_{3,i=1\to N_y} - k_2\right)^2}{b^2} \le 1 \\
\vec{h}_4(\vec{\kappa}) = \dfrac{\left(x_{3,i=1\to N_x} - h_1\right)^2}{a^2} + \dfrac{\left(y_{3,i=1\to N_y} - k_1\right)^2}{b^2} \le 1 \\
\vec{h}_5(\vec{\kappa}) = \dfrac{\left(x_{4,i=1\to N_x} - h_2\right)^2}{a^2} + \dfrac{\left(y_{4,i=1\to N_y} - k_2\right)^2}{b^2} \le 1 \\
\vec{h}_6(\vec{\kappa}) = \dfrac{\left(x_{4,i=1\to N_x} - h_3\right)^2}{a^2} + \dfrac{\left(y_{4,i=1\to N_y} - k_3\right)^2}{b^2} \le 1 \\
\qquad\qquad \vdots \\
\vec{h}_{N_c-1}(\vec{\kappa}) = \dfrac{\left(x_{N_c,i=1\to N_x} - h_{N_c-2}\right)^2}{a^2} + \dfrac{\left(y_{N_c,i=1\to N_y} - k_{N_c-2}\right)^2}{b^2} \le 1 \\
\vec{h}_{N_c}(\vec{\kappa}) = \dfrac{\left(x_{N_c,i=1\to N_x} - h_{N_c-1}\right)^2}{a^2} + \dfrac{\left(y_{N_c,i=1\to N_y} - k_{N_c-1}\right)^2}{b^2} \le 1
\end{cases} \tag{28}$$

Where N_c represents the number of constraints computed and can be obtained using

$$N_c = \frac{N_{wells}(N_{wells} - 1)\,\mathrm{N_s}}{2} \tag{29}$$

Whereas N_{wells} defines the number of wells to be placed in the reservoir.

Eq. 27, directs that the second well should not be located within the minimum interwell spacing area nearby the first well, it gives the first nonlinear constraint to be employed on the objective (cost) function. Besides, the position of the third well should be outside the minimum spacing adjacent to the locations of the first (x_1, y_1) and second wells (x_3, y_3) accordingly forming the second and third constraints respectively. Similarly, constraints are recurrent for each next well until all constraints have been clearly quantified as presented in Eq. 28. This approach tested the violation of constraints to be placed in the reservoir for every well against every other well. Obviously, the formulation of constraints in this manner will yield a number of constraints to be experienced equal to N_c as given in Eq. 29 (Awotunde 2014).

In this problem, the vertical sections of horizontal wells are also tested for spacing constraint along with the horizontal section. Moreover, if the two horizontal wells are placed on different layers their heel coordinates are tested for spacing constraint of vertical section of horizontal well using vertical well spacing constraint condition.

For vertical well, minimum well spacing is enforced using the equation of circle in the reservoir. Each individual well coordinates are tested on the well on which the circle is formed and on the subsequent well and the well coordinates of other wells are checked till the count of number of constraints is achieved.

$$(x_i - h_j)^2 + (y_i - k_j)^2 = r^2 \tag{30}$$

Where (h_j, k_j) represents the coordinates of well on which the circle is formed. Each well (x_i, y_i) is tested on the following equation:

$$D_{vp} = \left(x_i - h_j\right)^2 + \left(y_i - k_j\right)^2 - r^2 \tag{31}$$

If $D_{vp} \leq 0$, it means the well is lying inside the drainage area of other well and it will be considered as a violation of spacing. Actually, the constraints specified that $\left(x_2 - x_1)^2 + (y_2 - y_1\right)^2$ should be greater than or equal to r^2. The constraints are tested in the same manner as defined above for the horizontal well. Any individual well location $\left(x_1, y_1\right)$ from the starting well, the subsequent ordered constraints should be placed on every well:

$$\begin{cases} \vec{h}_1(\vec{\kappa}) = \left(x_2 - x_1)^2 + (y_2 - y_1\right)^2 - r^2 \leq 0 \\ \vec{h}_2(\vec{\kappa}) = \left(x_3 - x_1)^2 + (y_3 - y_1\right)^2 - r^2 \leq 0 \\ \vec{h}_3(\vec{\kappa}) = \left(x_3 - x_2)^2 + (y_3 - y_2\right)^2 - r^2 \leq 0 \\ \vec{h}_4(\vec{\kappa}) = \left(x_4 - x_1)^2 + (y_4 - y_1\right)^2 - r^2 \leq 0 \\ \vec{h}_5(\vec{\kappa}) = \left(x_4 - x_2)^2 + (y_4 - y_2\right)^2 - r^2 \leq 0 \\ \vec{h}_6(\vec{\kappa}) = \left(x_4 - x_3)^2 + (y_4 - y_3\right)^2 - r^2 \leq 0 \\ \qquad\qquad \vdots \\ \vec{h}_{N_c-1}(\vec{\kappa}) = \left(x_{N_c} - x_{N_c-2})^2 + (y_{N_c} - y_{N_c-2}\right)^2 - r^2 \leq 0 \\ \vec{h}_{N_c}(\vec{\kappa}) = \left(x_{N_c} - x_{N_c-1})^2 + (y_{N_c} - y_{N_c-1}\right)^2 - r^2 \leq 0 \end{cases} \tag{32}$$

Where N_c can be calculated using

$$N_c = \frac{N_{wells}(N_{wells} - 1)}{2} \tag{33}$$

4.4.2 Solution Methodology: Penalty Approach

There are many methods for handling COP present, it converts the constrained problem to an unconstrained one by adjusting the objective function, either its penalty parameters or the Lagrange multipliers. In this work, the penalty method was opted for to solve the COP presented in Eqs (34) and (35). The use of the penalty method is to transform unconstrained optimization algorithms into constrained optimization case by adding a term that comprises of the penalty parameter and a measure of violation of the constraints to the objective function. The value of the penalty term is a positive value and it upsurges as the iteration increases so that as the solution proceeds it becomes increasingly difficult for the algorithm to accept an infeasible solution. The measure of violation is a function of constraint that gives a value of zero when no constraint is violated and nonzero value if any of the constraints is violated. At any iteration $\vec{\kappa}$, the objective function of the unconstrained optimization problem can be expressed as

$$f(\vec{\kappa}, \dot{\varsigma}) = f(\vec{\kappa}) + \sum_{j=1}^{N_c} \dot{\varsigma}_{k,j} \left[h_{k,j}\left(\vec{\kappa}\right) \right]^s \tag{34}$$

Condition to:

$$\dot{\varsigma}_{k,j} = \begin{cases} 0 & if \quad g \leq 0 \\ \varsigma_k \gg 0 & if \quad g > 0 \end{cases} \tag{35}$$

Where $\dot{\varsigma}_k$ is a scalar quantity which increases monotonically and given by the user. In Eq. 34, s is commonly used as 1 or 2 (Coello 1999; Byrne 2008). In this study, the value of s was chosen as 1. The value of $\dot{\varsigma}_k$ defines the performance of the solution algorithm. For smaller values of $\dot{\varsigma}_k$, the algorithm spends too much time searching the infeasible region of the problem space and most likely converges to an infeasible solution. While on the other hand, larger values of $\dot{\varsigma}_k$ makes the algorithm to move quickly into a feasible region and consequently converge to a feasible solution space which have a possibility of being suboptimal. The value of $\dot{\varsigma}_k$ should be selected carefully to adequately search the optimal solution in the problem space. Also, $f(\vec{\kappa}, \dot{\varsigma})$ can be reflected as a multi-objective function constituting of cost function $f(\vec{\kappa})$ and penalty function $\sum_{j=1}^{N_c} h_j$ with $\dot{\varsigma}_k$ being the weighting parameter that controls the two objectives such as only the influence of the primary objective $f(\vec{\kappa})$ is taken into account if the value of $\dot{\varsigma}_k$ is zero. On the other hand, the effect of the secondary objective $\sum_{j=1}^{N_c} h_j$, becomes more significant as the value of $\dot{\varsigma}_k$ increases. Consequently, the result showed the relative importance placed on the constraints $\vec{h}_j$. It is suggested to find the values of $\dot{\varsigma}_k$ based on the problem objectives such as lower values of $\dot{\varsigma}_k$ gives better performance of the primary objective with the possibility that a constraint might be violated. While the higher values of $\dot{\varsigma}_k$ ensure the violation of the constraints is very low with poorer values of the primary objective obtained. When the constraints are crucial (e.g. constraints that must never be violated), then bigger values of $\dot{\varsigma}_k$ should be selected to reflect the criticality of the constraint. Conversely, when the constraints are not critical just only desirable, then smaller values of $\dot{\varsigma}_k$ can be used.

4.5 Implementation

In this study, the effectiveness of the solution on a heterogeneous reservoir was tested. The population size in the PSO was obtained using Eq. 1 and the algorithm was run for over 2000 functions evaluation. In all the cases presented, an augmented objective function composed of the NPV and the penalty values (after both have been properly scaled) is used instead of NPV (or -NPV in a minimization process). Each particle in the population has one NPV value and corresponding penalty values. The median fitness (objective) in the population was chosen at the first generation as the scaling factor for NPV and mean value for penalty. However, we observed in some cases the values of the objective function as infinity if median fitness of penalty values were used as scaling factor because of the possibility of no violation of the penalty constraint. Conversely, other statistical parameters such as the mean or maximum value in the population can be used for NPV scaling. The price and costs functions were assumed to be constant throughout the operating duration.

4.5.1 Example: Reservoir with Distributed Permeability Field

This example demonstrates a synthetic reservoir with a fully distributed permeability field used for numerical simulation of SAGD and VAPEX processes, log permeability distribution is shown in Figure 12. The reservoir model is divided into 32x32x10 grid cells. The dimension of each grid in x and y direction is 200 ft. while in z direction it is 8.2 (2.5m) ft. The porosity of both models are different in different layers but within the layer it remain constant, the distribution is shown in Figure 11. The pertinent fluid and fluid-rock properties can be shown in Figure 13 - Figure 15. The reservoir properties of both SAGD and VAPEX models are shown in Table 2 (Azad and Awotunde, 2014). The producing duration of both SAGD and VAPEX processes were considered as 10 years in the optimization problem. The steam quality of eighty five percent (85 %) and injection temperature of four fifty degree Fahrenheit (450 ˚F) is used. The simulation of SAGD process to commence effectively it is necessary to preheat both injector and producer with the help or either steam injection or heater. The preheating of the grid blocks connected to wells creates communication of fluids in the vicinity of wells and helps in mobilizing of oil towards producer. It was reported that the heating period should be uniform otherwise it will cause failure to the SAGD process (Kazemi, 2010). To simulate the heating period, heaters are used in the simulator (Eclipse 300, Thermal). The heating rate of 4E6 Btu/day and preheating period of 60 days were used in SAGD simulations.

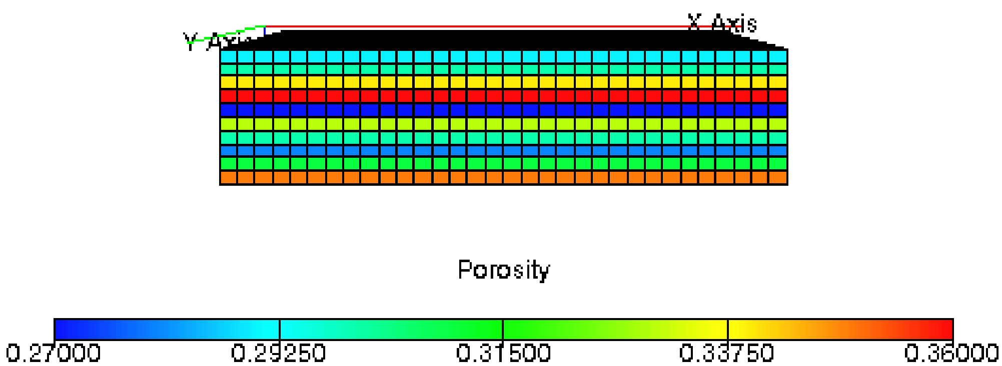
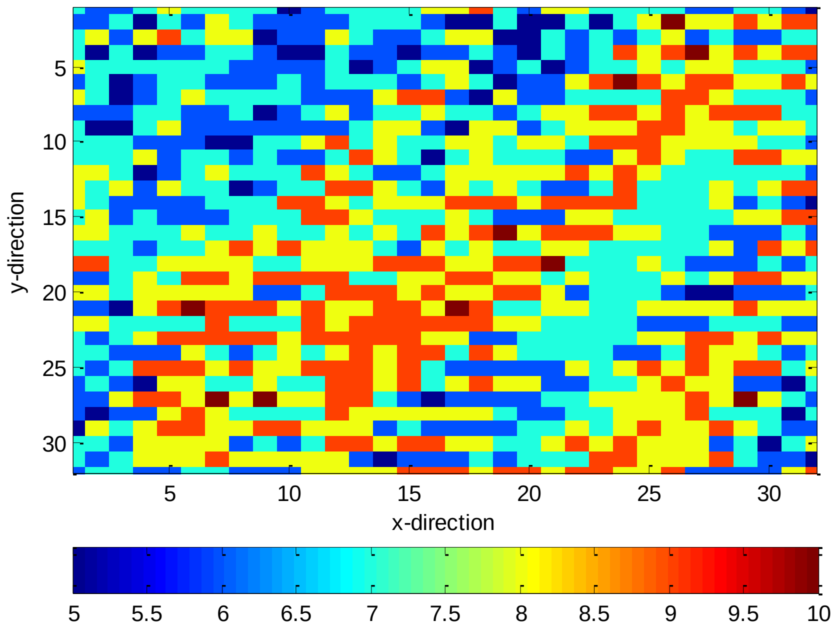


Figure 11: Porosity distribution in z-direction for both models (SAGD and VAPEX)



y-direction
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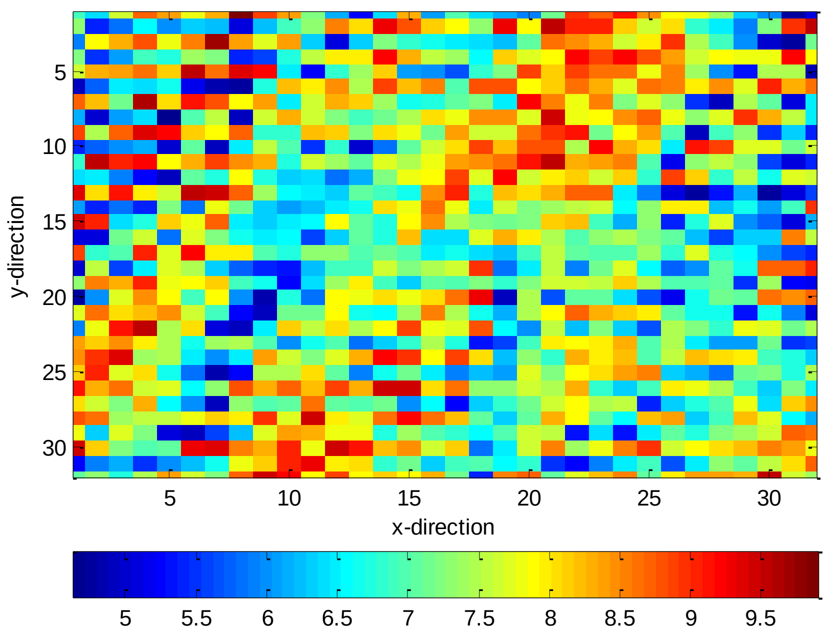
(L_1)



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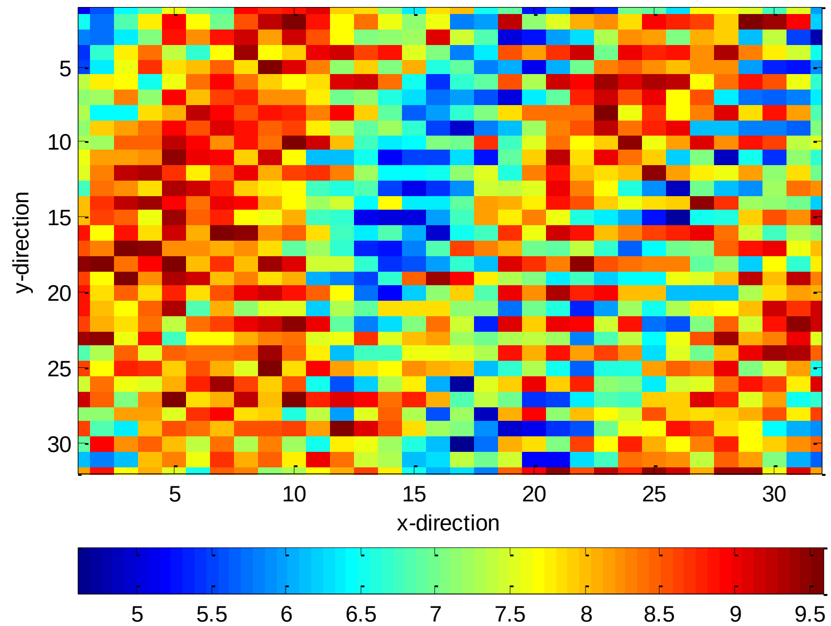
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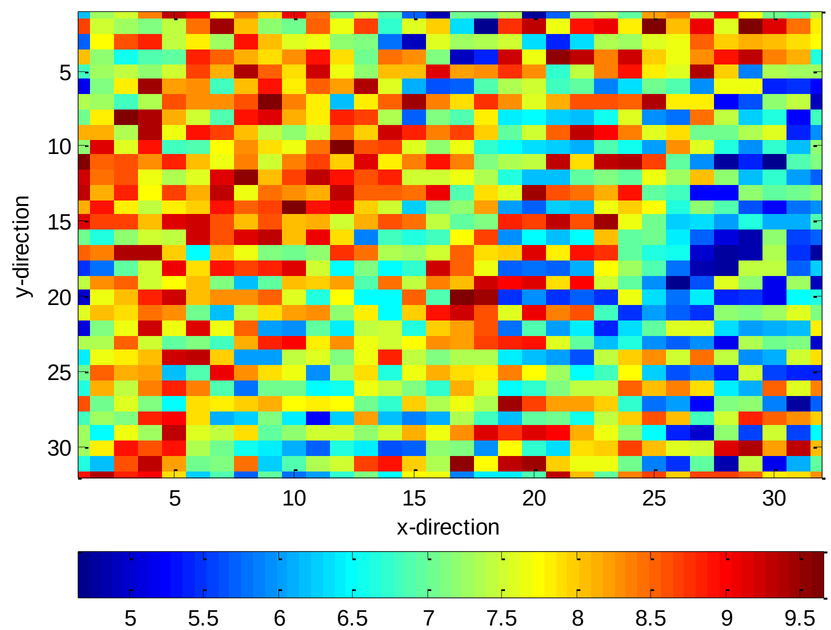
(L3)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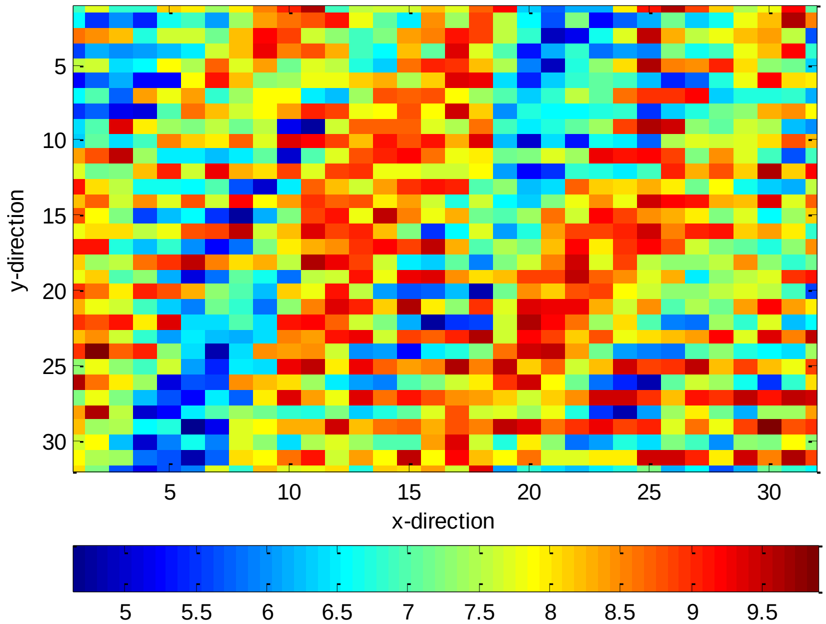
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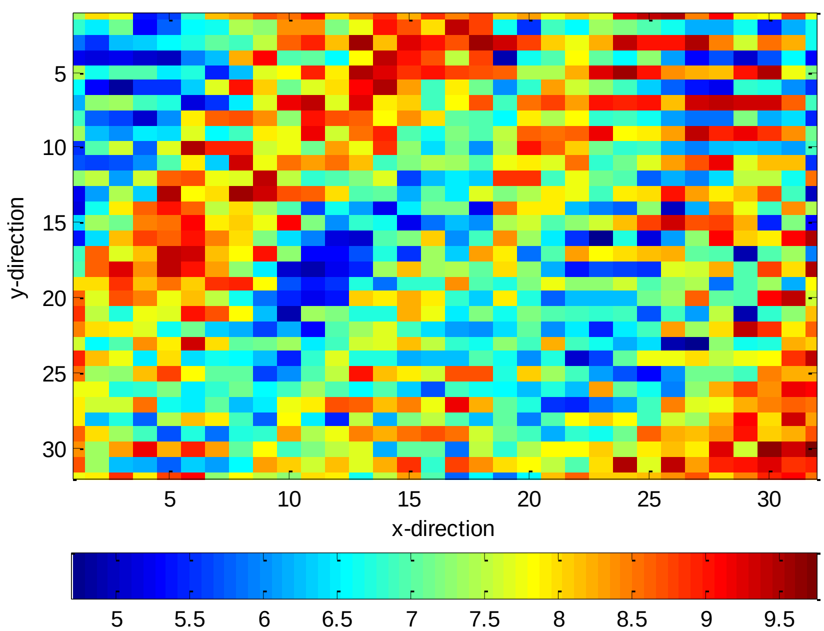
(L_5)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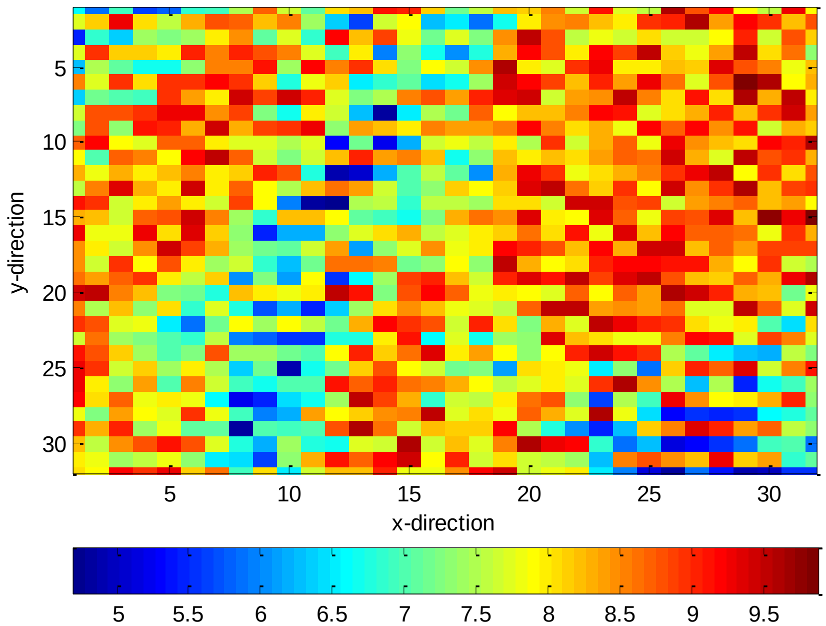
(L_6)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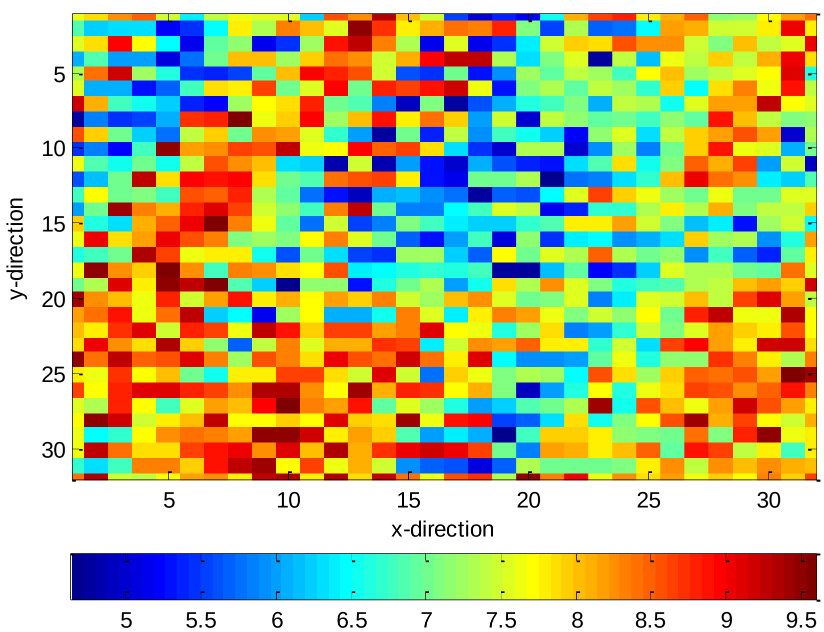
(L_7)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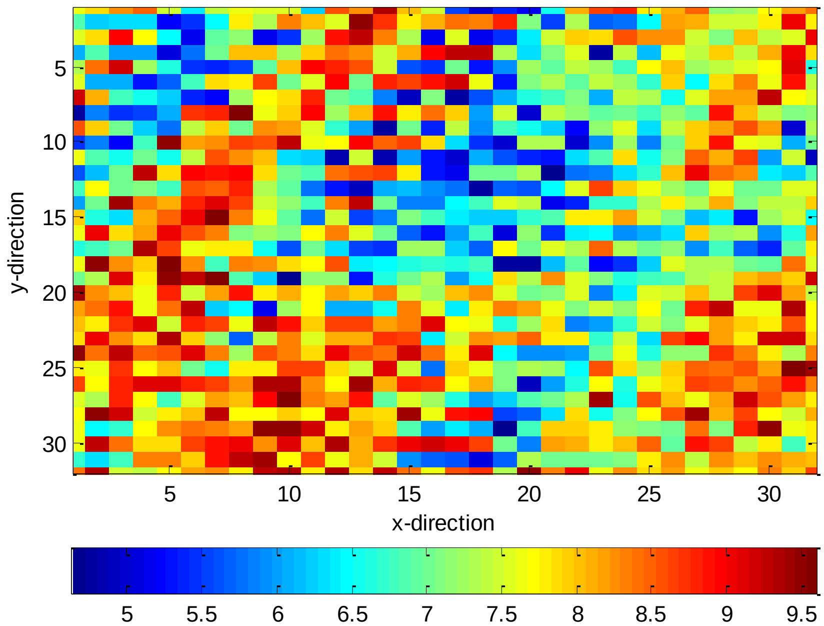
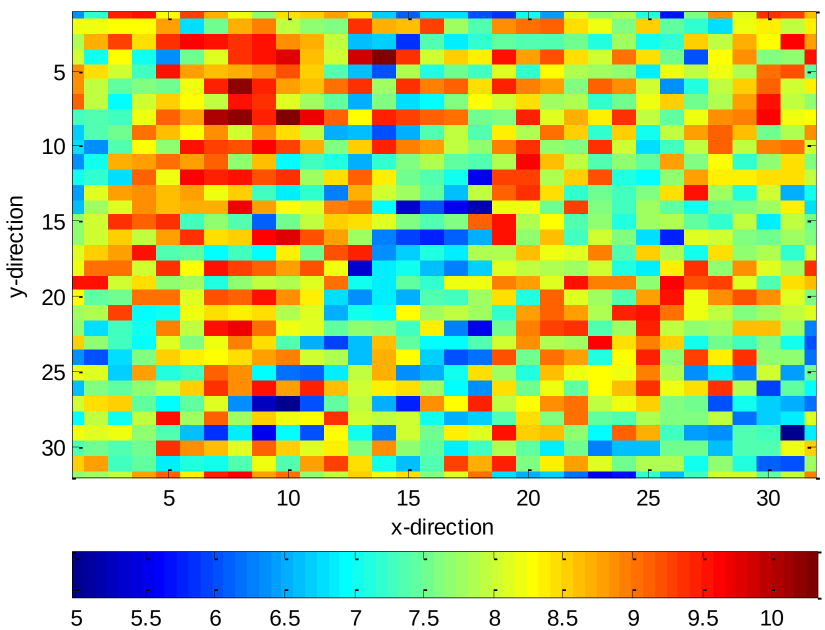
(L_8)



(L_9)



(L_{10})

Figure 12: Permeability distribution of each layer (L_1-L_{10}) for both SAGD and VAPEX

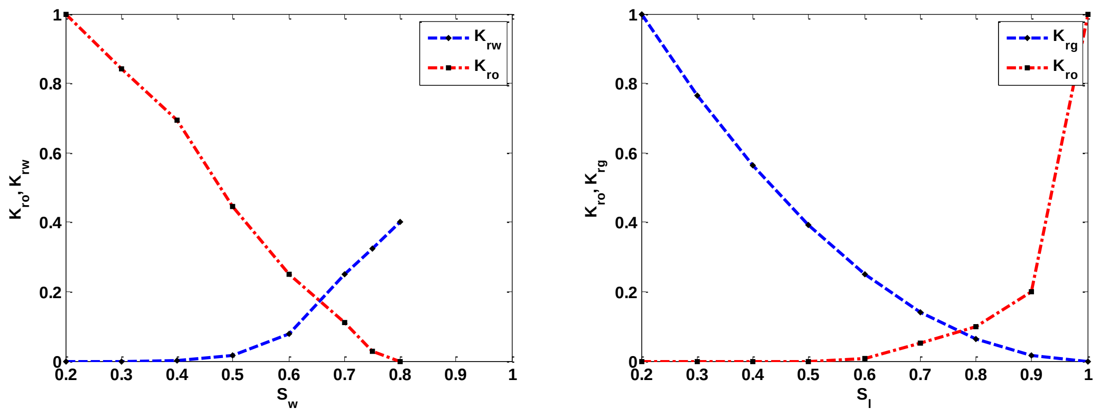


Figure 13: Relative permeability curves used for both models (SAGD and VAPEX)

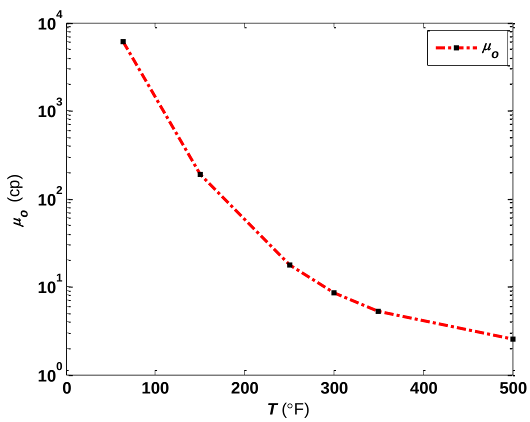
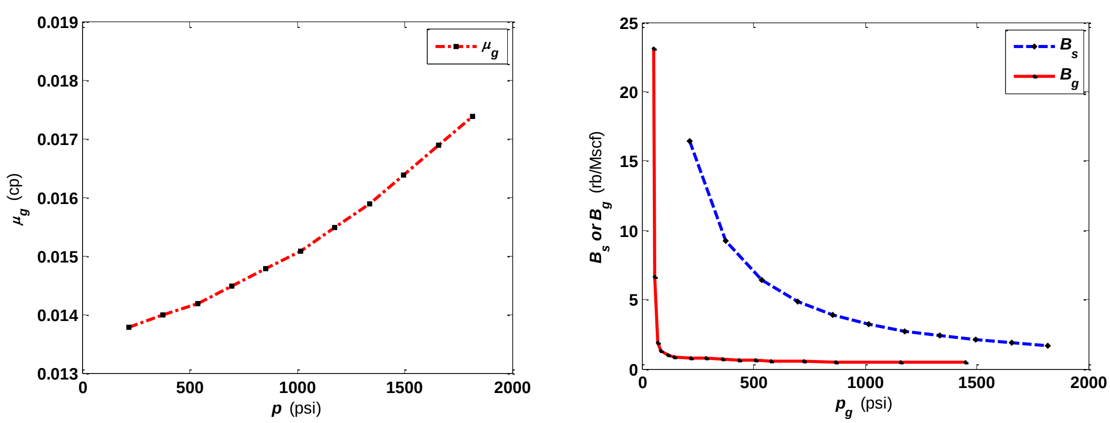


Figure 14: Viscosity temperature relation for SAGD Model



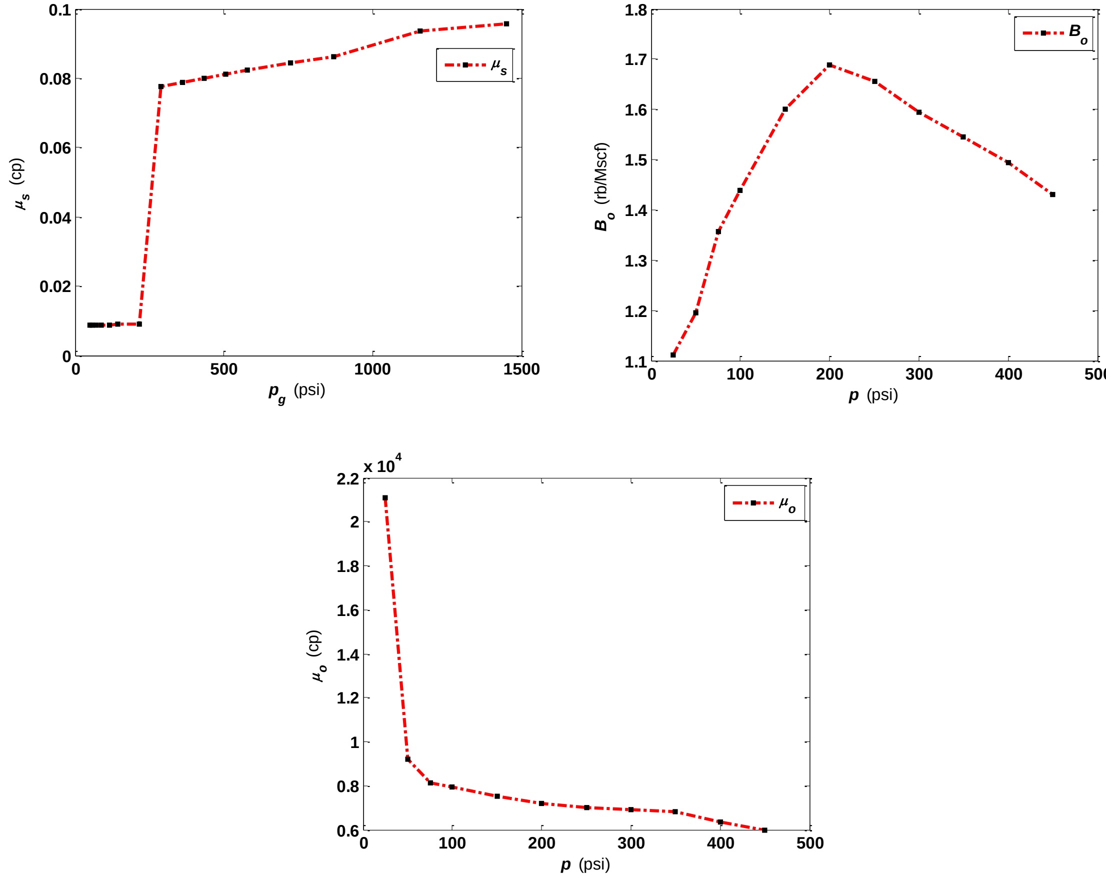


Figure 15: Fluid Properties of gas, oil, and solvent used in VAPEX Model

Table 2: Properties used in SAGD and VAPEX models

Reservoir Properties	
Reservoir Depth	396 m
Reservoir Thickness	25 m
Average Porosity	31.30 %
Oil Viscosity* (RC)	6000 cp
Oil Saturation	0.80
Initial Pressure	450 psi
Initial Temperature	64.4 ˚F
Oil Density* (RC)	20 API
Thermal Conductivity	33 Btu/ft/day/˚F
Rock Heat Capacity	41 Btu/ft^3/˚F
Overburden Thermal Conductivity	30 Btu/ft/day/˚F
Overburden Volumetric Heat Capacity	38 Btu/ft^3/˚F

In this work, the key objective is to optimize horizontal well placement and well rates. These operational variables are to be estimated simultaneously. The maximum allowable well length is specified to be 2500 ft. A minimum well spacing of 10 acres were enforced around each vertical well while the tolerance between the end points of the horizontal well to the vertex of ellipse were imposed of 10 acres for searching the optimal well placement and a maximum value of penalty parameter were used as 5. The area corresponding to ellipse is dependent on the length of horizontal well which is a variable quantity and is calculated in the optimization problem. This tolerance ensures at least one grid block spacing between any two adjacent wells. Beyond this area, the optimizer should be left to determine the optimal location of the wells. It is recommended to have a minimum 5 to 10 acre spacing to prevent the well from any cause of damage to existing wells (Awotunde 2014). This well spacing constraint were imposed for all cases. The number of constraints to be evaluated for horizontal and vertical well were obtained using Eq. 30 and 34 correspondingly.

In this study, the optimization is performed on three different cases of both SAGD and VAPEX models.

4.5.2 Case 1: Optimization of Horizontal Well Pairs

This case deals with the optimization of horizontal well pairs used to produce heavy oil. In this case, optimization variables are defined as two parameter for heel coordinates, one for the layer, and one for length of in the optimization problem. Since both the injector and producer are placed parallel to each other and have a vertical separation of five to fifteen meters (5 to 5 m), only the location of one horizontal well can be used to place both wells. The vertical separation of seven and half meters is used in this case. The vertical separation is added to the layer parameter of injector well obtained from optimizer and the other parameters of injector wells remains same to place producer. In this case, the total five well pairs were optimized which were represented by twenty five decision variables.

The production wells were controlled under a specified total liquid rate (250 stb/day) constraint. However, a secondary control of minimum bottomhole pressure (BHP of 75 psi) was enforced to ensure reservoir produces above bubble point pressure. Each injection well was controlled under a defined water rate which was injected in the form of steam (250 stb/day) while maintaining a maximum BHP limit of 1150 psi. In case, any well pressure goes above the maximum BHP limit, the operating constraint switched from fixed injection rate to fixed pressure constraint to ensure it below formation fracture pressure limit.

4.5.3 Case 2: Optimization of Injection and Production Rates with Horizontal Well Pair Location

The optimization of injection and production rates were performed simultaneously. In this case, optimization variables are defined as two parameter for heel coordinates, one for the layer, and one for well length and two parameter for injection and production rates of optimization problem. The same methodology as described in Case 1 for well pair placement was used. The vertical separation of seven and half meters was applied in this case. The total five well pairs containing ten wells were optimized. In this case, the total five parameters for each well pairs and one rate parameter of each well were optimized which were represented by thirty five decision variables.

4.5.4 Case 3: Optimization of Vertical Separation, Injection and Production Rates with Horizontal Well Pair Location

In this case, the vertical separation between injector and producer, injection and production rates, and well locations of the injector and producer were optimized simultaneously. The optimization variables were defined as two parameters for heel coordinates, one for the layer, and one for well length, one for vertical separation and two parameters for injection and production rates of optimization problem. The same methodology as described in Case 1 for well pair placement was used. The number of well pairs were same as Case 1 and 2. In this case, the total six parameters for each well pairs and one rate parameter of each well were optimized that were represented by forty design variables.

CHAPTER 5

RESULTS AND DISCUSSION

This section presents the result of both SAGD and VAPEX process optimization for all three cases. The comparison of both process were conducted along with the difference in the three cases. The yardstick of performances were chosen solely as the net present value attained in the optimization scheme for all the different cases presented. Those cases were arbitrated to perform better which have higher NPV than that with a lower NPV if the constraints of well spacing were satisfied. To account for statistical variations and non-uniqueness of the process, each case were run five times using five different sets of random numbers in the PSO algorithm. The results showed five sets of possible solutions to the optimization problem for each case considered. In the performance analysis, only the best, median and worst realizations were used for comparison.

Figure 16 shows the net present value with respect to function evaluations performed to find the optimum solution for different realization of Case 1 in SAGD. It can be seen from the plot that forth realization give the best net present value (39 MM$) and the first realization was found to be median of the five realization which gives net present value (37.5 MM$) whereas the worst solution obtained in fifth realization having the net present value (34 MM$).

Figure 17 shows the optimal horizontal well locations pairs in SAGD Case 1, which gives best result in terms of net present value. Figure 18 shows the 2-D view of horizontal wells in each layer with permeability distribution.

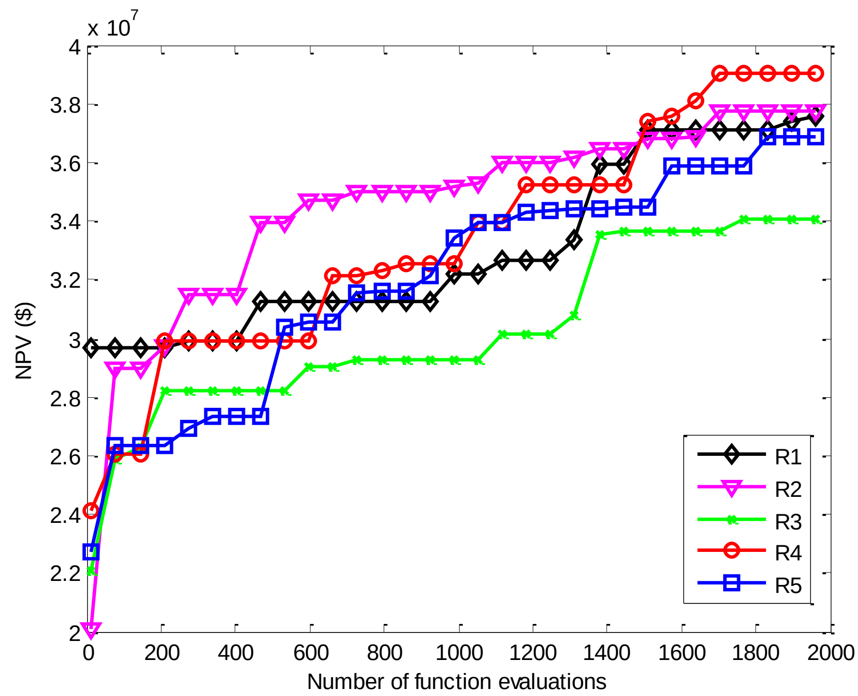


Figure 16: NPV comparison of different realization of Case 1 in SAGD

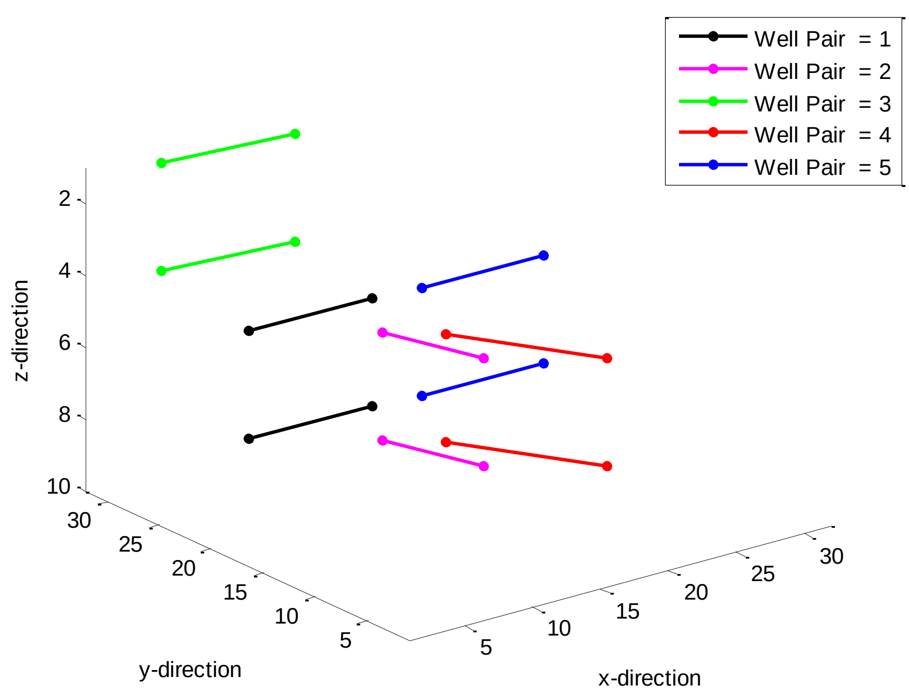
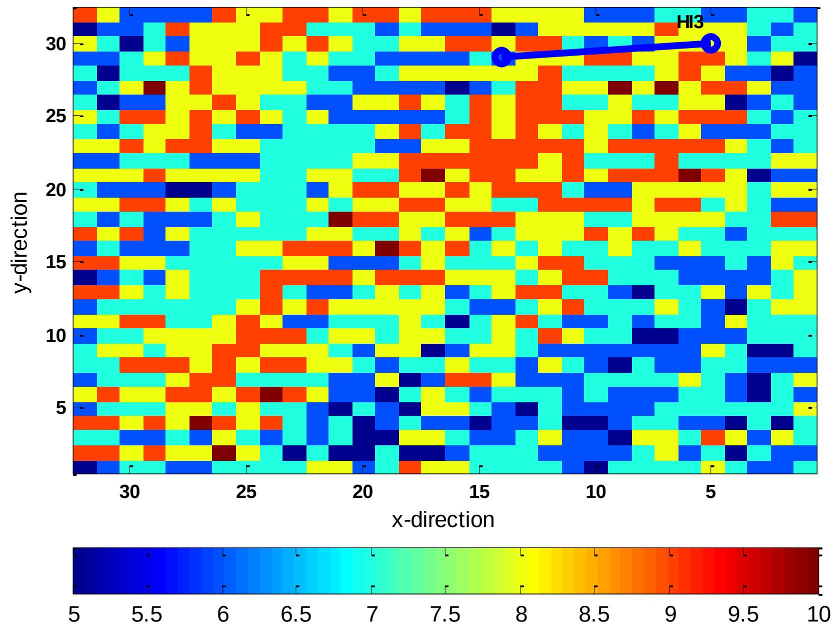


Figure 17: Best solution representation of for well location in 3D, Case 1


HI3
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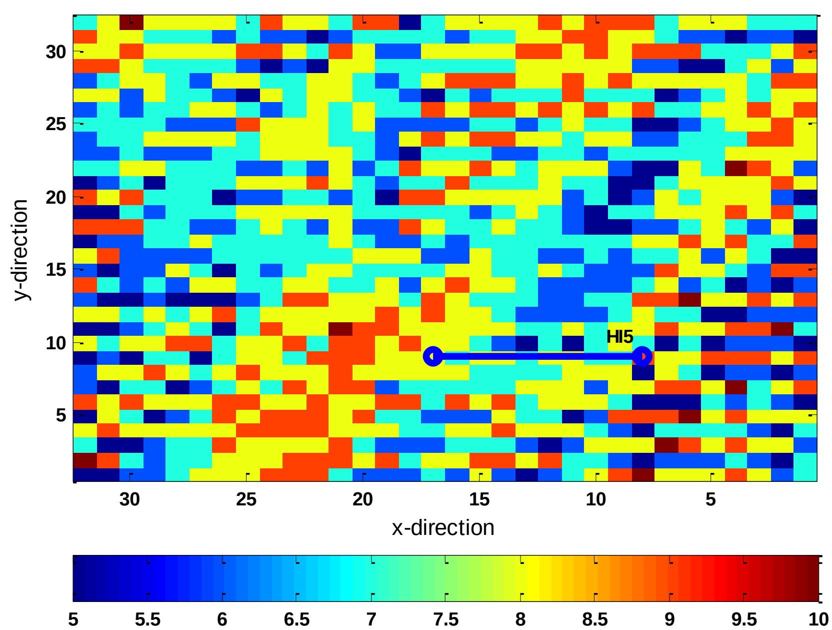
(a)


HI5
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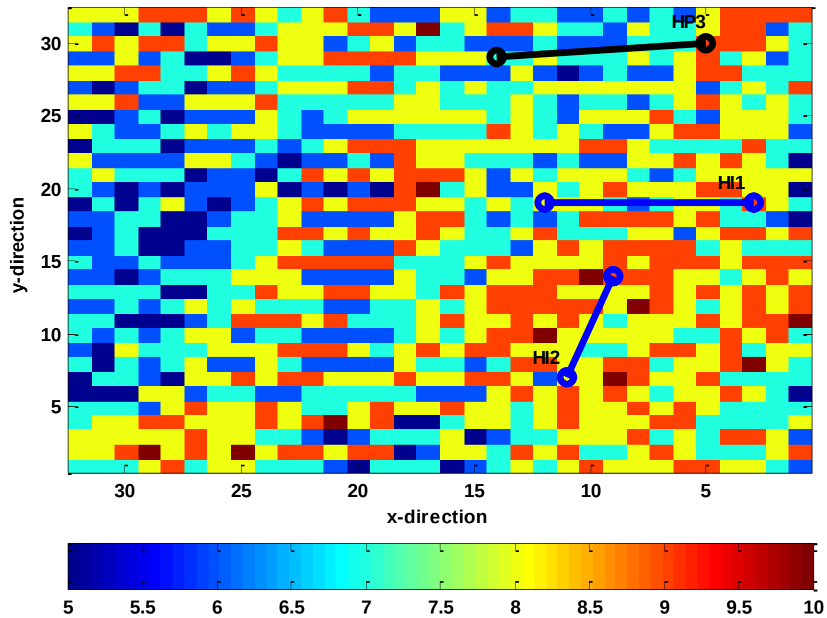
(b)


HP3
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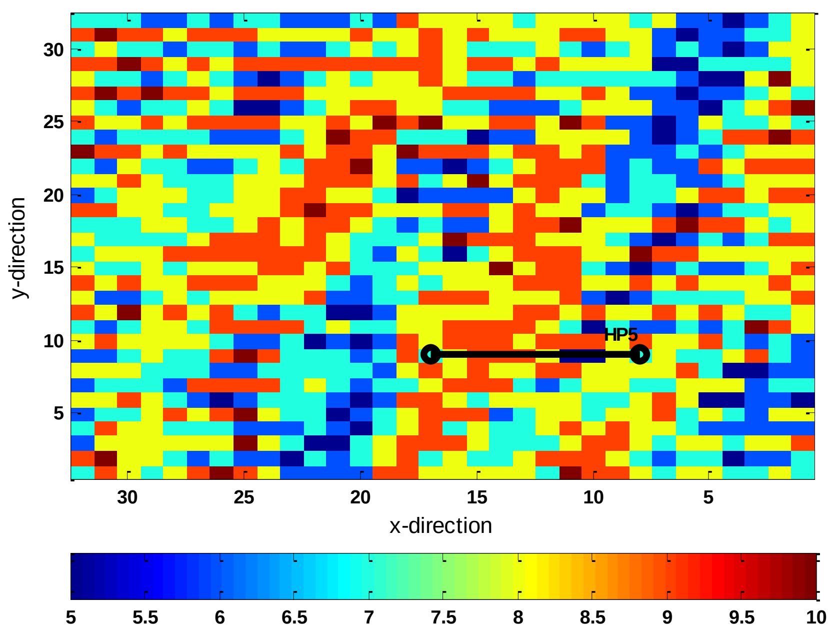
(c)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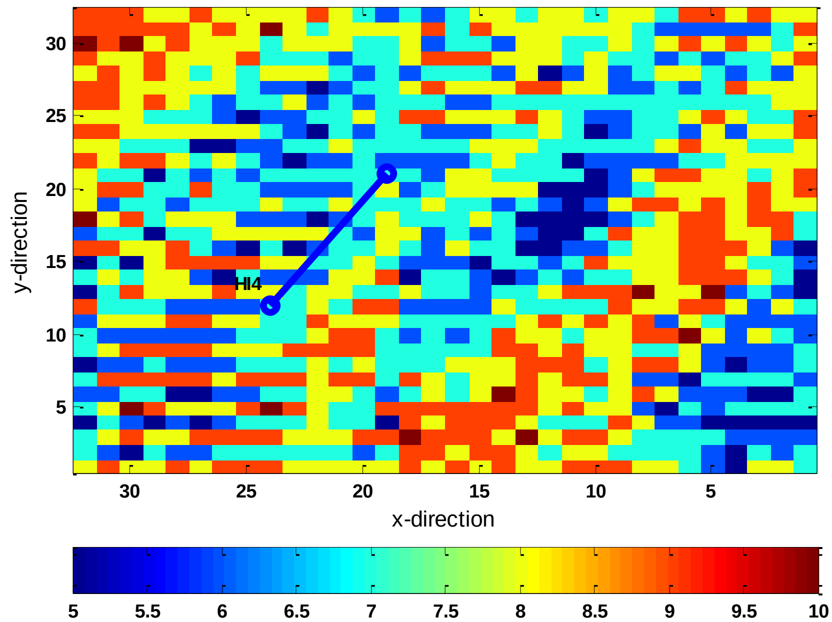
(d)


HI4
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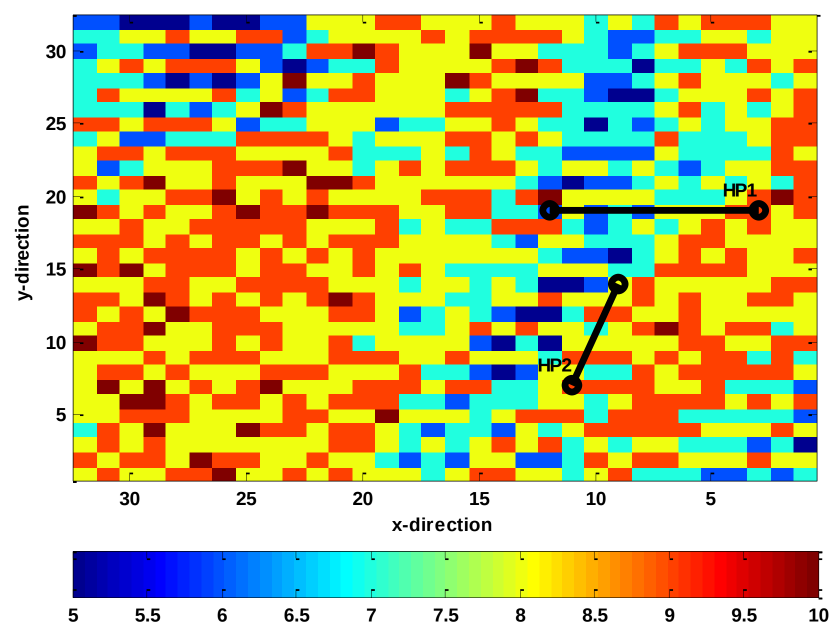
(e)


HP1
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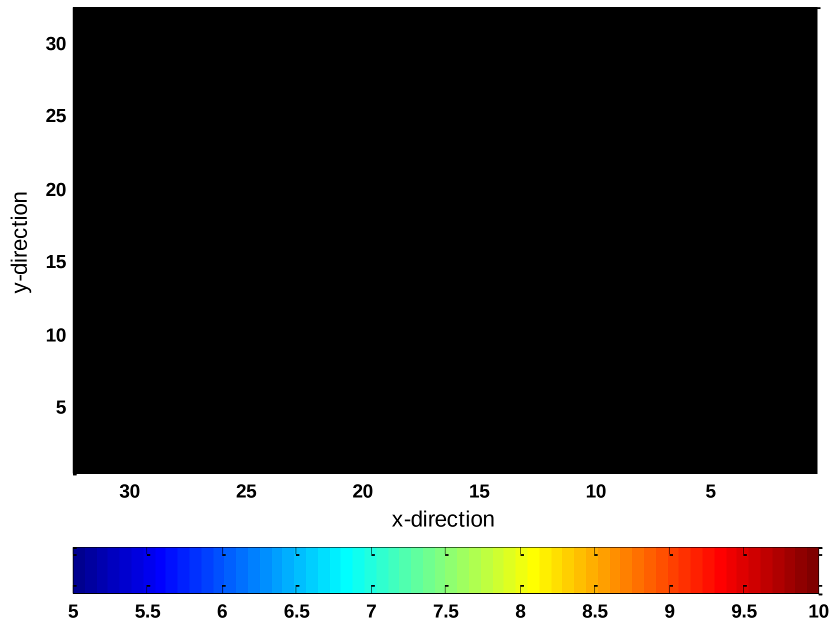
(f)



(g)

Figure 18: Best solution well location of SAGD model in 2D (x-y plane) for Case 1, (a) Layer 1 (b) Layer 2 (c) Layer 4, (d) Layer 5, (e) Layer 6, (f) Layer 7, (g) Layer 9

It was observed that horizontal wells injectors and producers were placed at the heterogeneous sections of the reservoir. It was due to the fact that if both types of wells are placed at high permeable zone than there is a chance of severe water production or live steam comes from the production well, similarly if both types of wells are placed at very low permeability of the reservoir then there would be low productivity of the well.

Figure 19 shows the net present value versus function evaluations plot for different realization of Case 2 in SAGD. It was seen that the third realization outperformed other realizations giving net present value (276 MM$), and the median net present value (260 MM$) was found in the second realization, whereas the worst solution was obtained in first realization net present value (220 MM$).

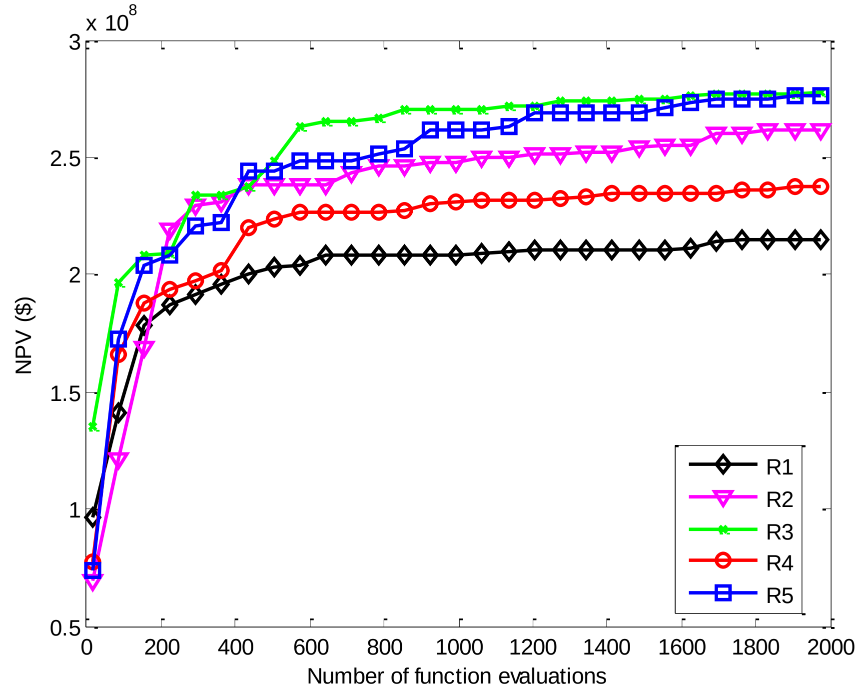


Figure 19: NPV comparison of different realization of Case 2 in SAGD

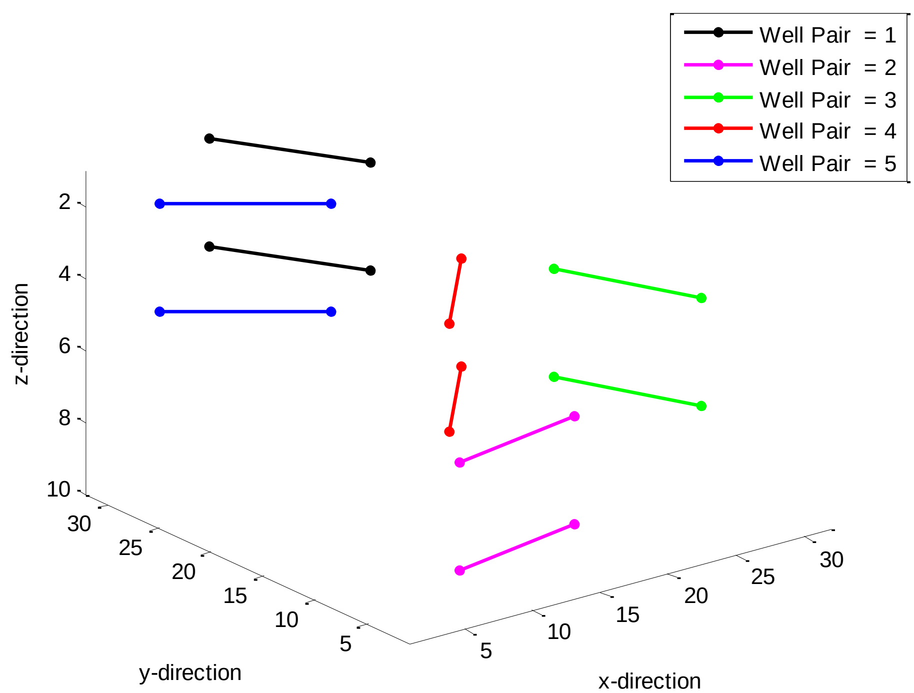
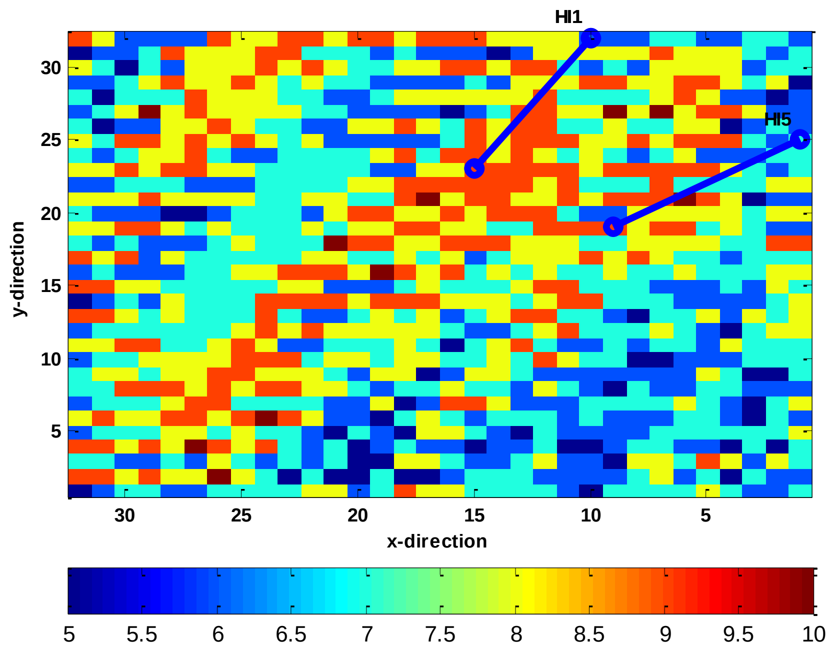


Figure 20: Best solution representation of for well location in 3D, Case 2


HI1
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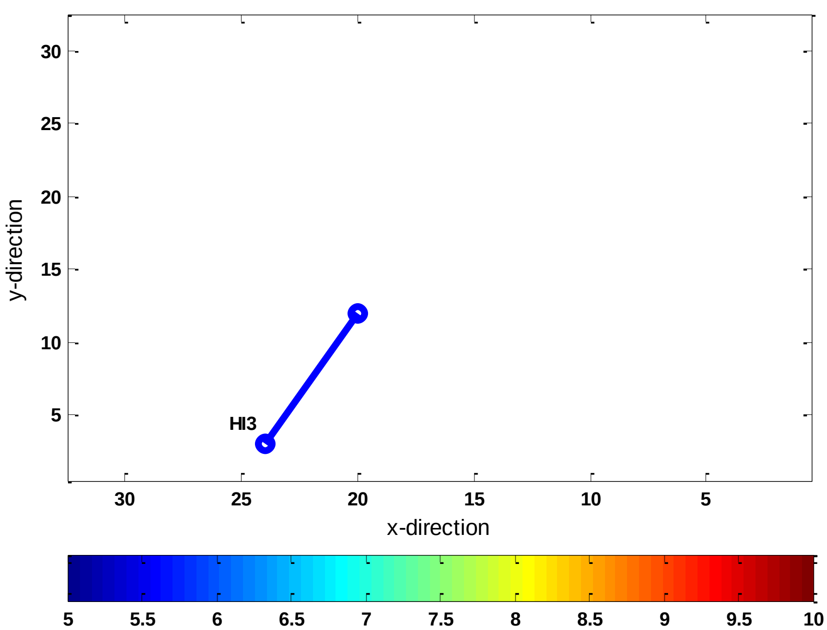
(a)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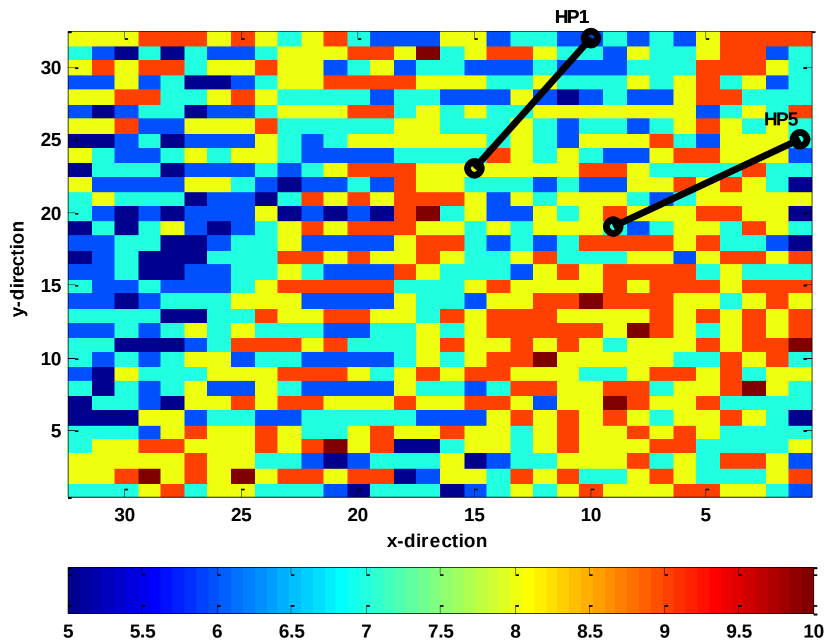
(b)



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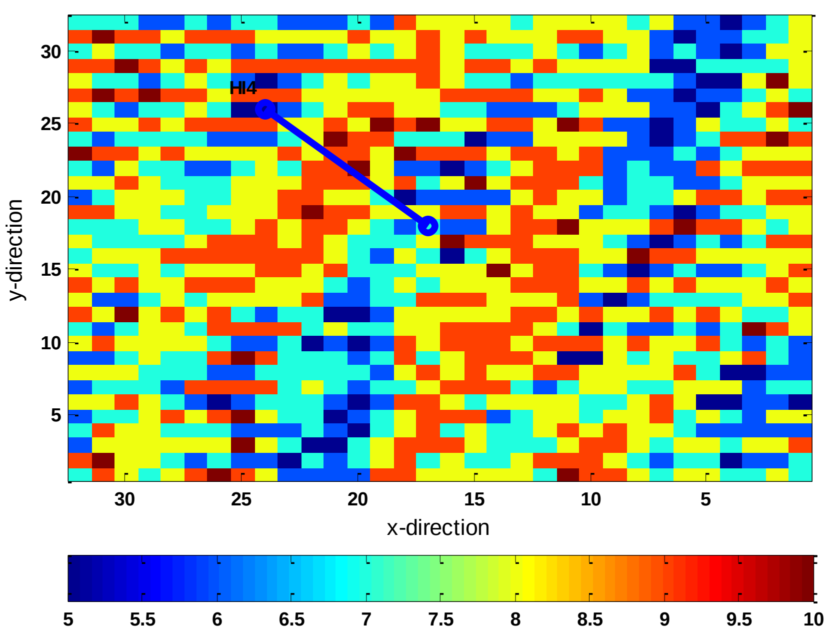
(c)



HI4
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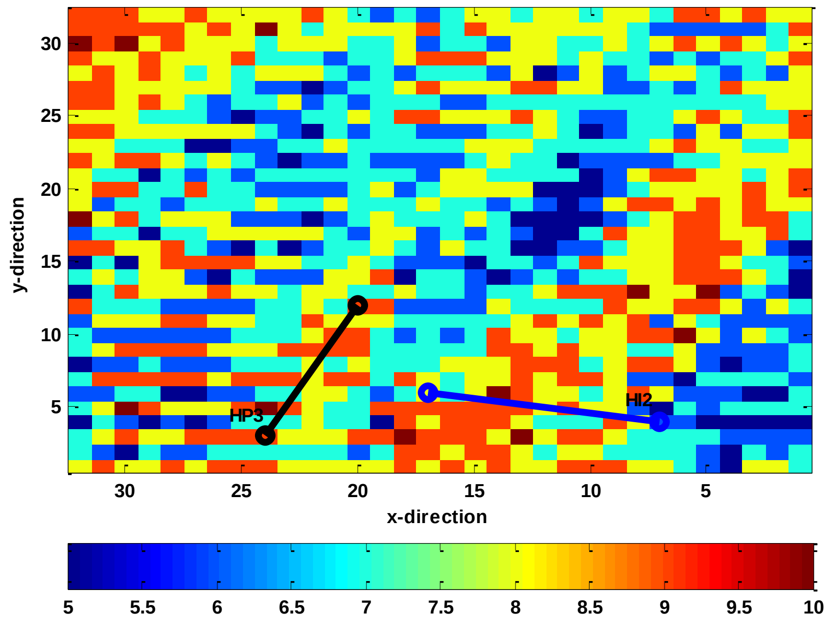
(d)



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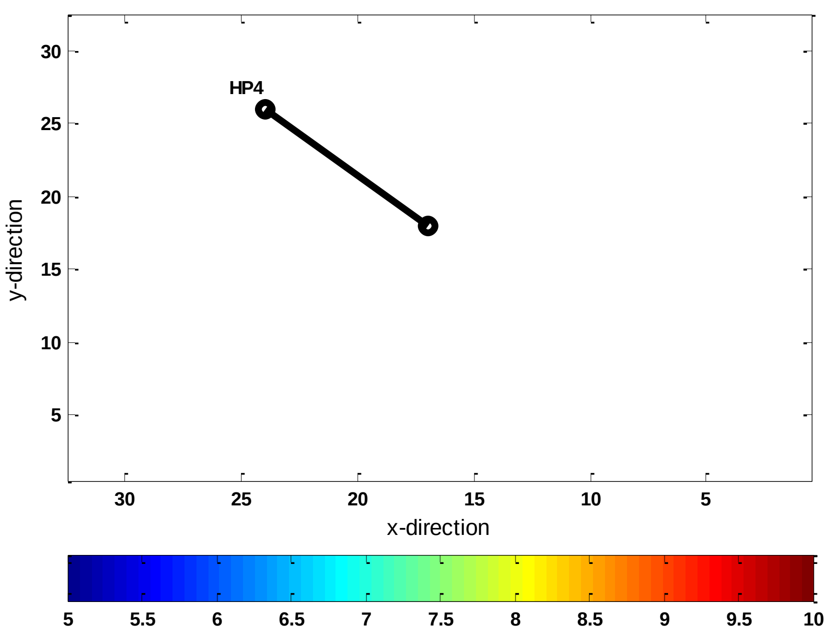
(e)



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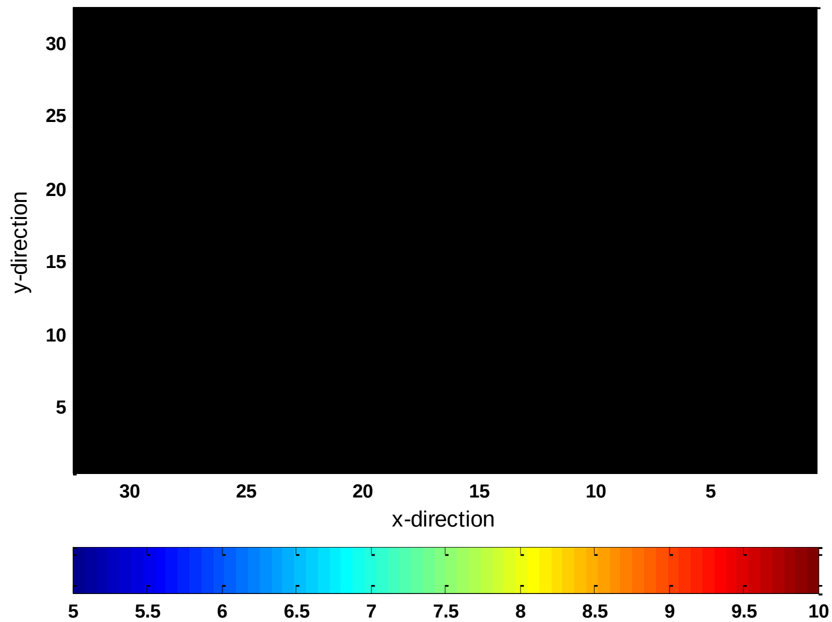
(f)



(g)

Figure 21: Best solution well location of SAGD model in 2D (x-y plane) for Case 2, (a) Layer 1 (b) Layer 3 (c) Layer 4, (d) Layer 5, (e) Layer 6, (f) Layer 8, (g) Layer 9

The optimal horizontal well locations pairs of SAGD for Case 2 is shown in Figure 20, which gives best result in terms of net present value. Figure 21 shows the 2-D view of horizontal wells in each layer with permeability distribution. Figure 21 shows that horizontal wells injectors and producers are placed at heterogeneous sections of the reservoir. It is due to the fact that if both types of wells are placed at high permeable zone than there is a possibility of severe water production from the producers, similarly if both types of wells are placed at very low permeability of the reservoir then there would be low productivity of well.

Figure 22 shows the net present value obtained with reference to function evaluations for different realization of Case 3 in SAGD. The highest net present value (265 MM$) was obtained in the first realization, realization 5 offers the median net present value (250 MM$), and the fourth realization shows the lowest net present value (235 MM$).

For the best solution, the optimal horizontal well locations pairs in SAGD Case 3 is presented in Figure 23. The 2-D plot of horizontal wells in each layer with permeability distribution is plotted to observe the spacing constraint. It was found that all production and injection wells were well spaced.

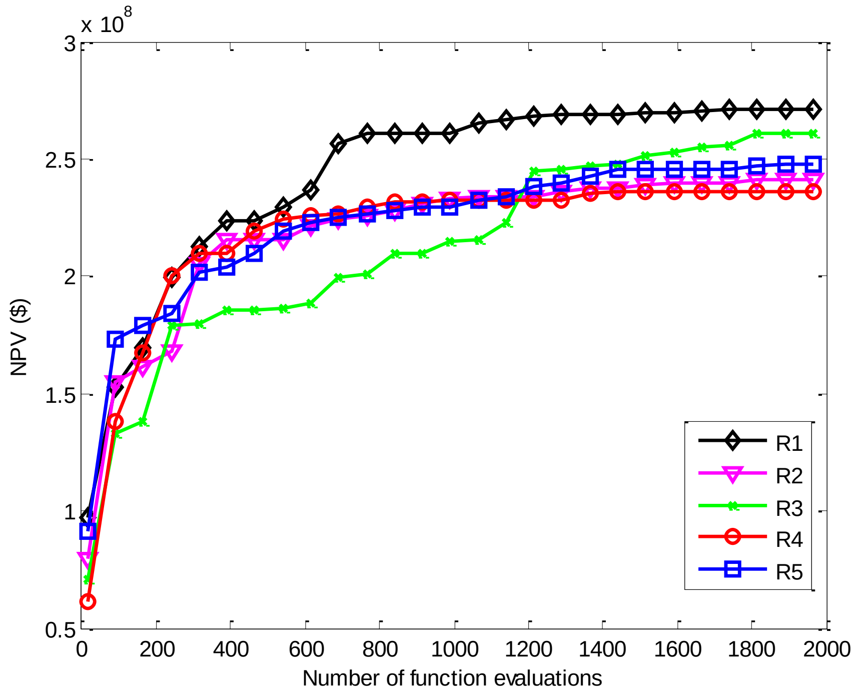


Figure 22: NPV comparison of different realization of Case 3 in SAGD

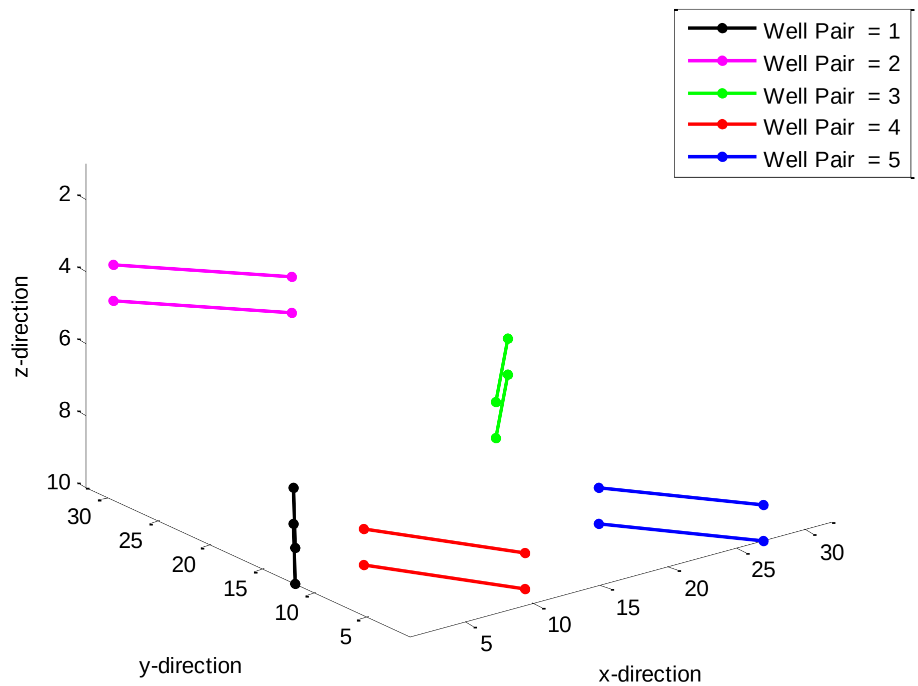
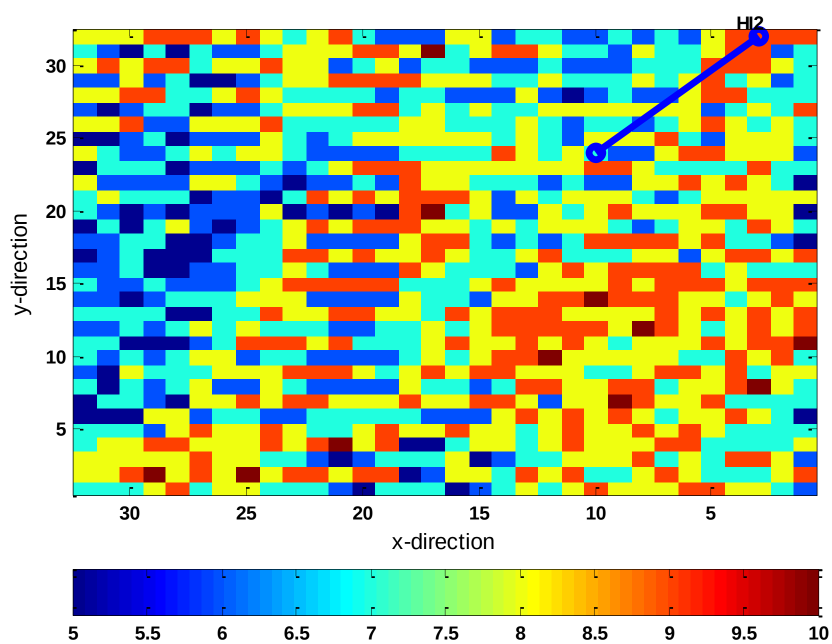
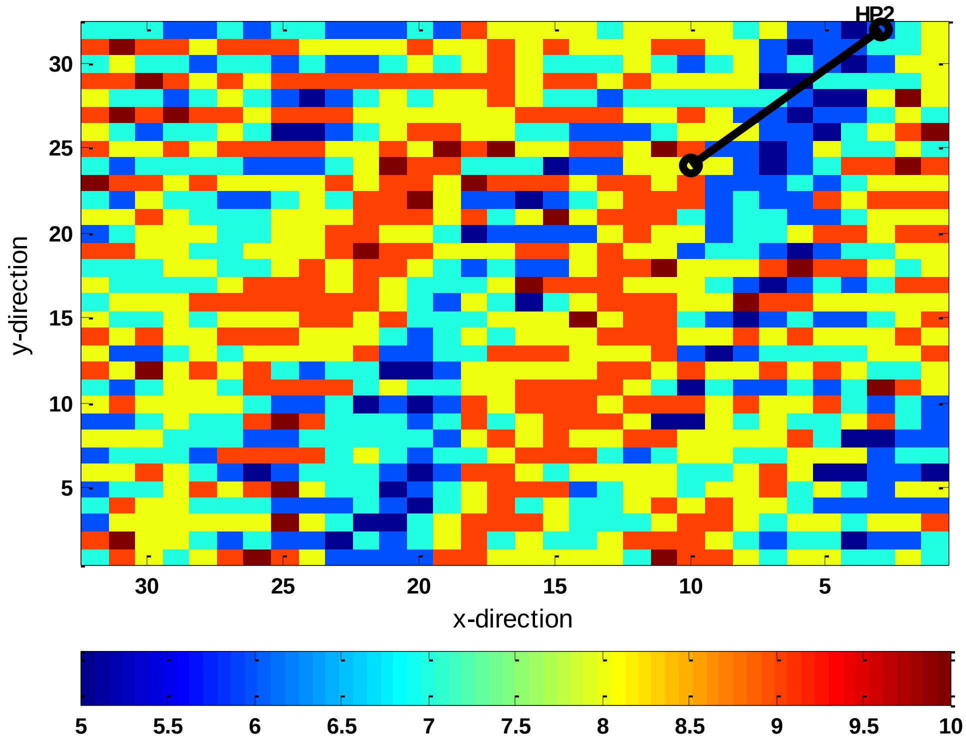


Figure 23: Best solution representation of for well location in 3D, Case 3



(a)


HP2
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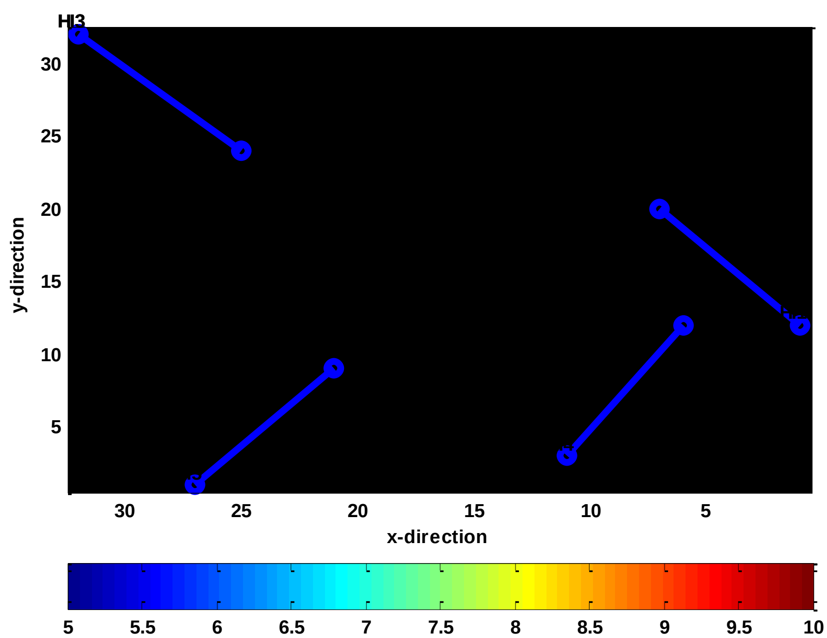
(b)


HI3
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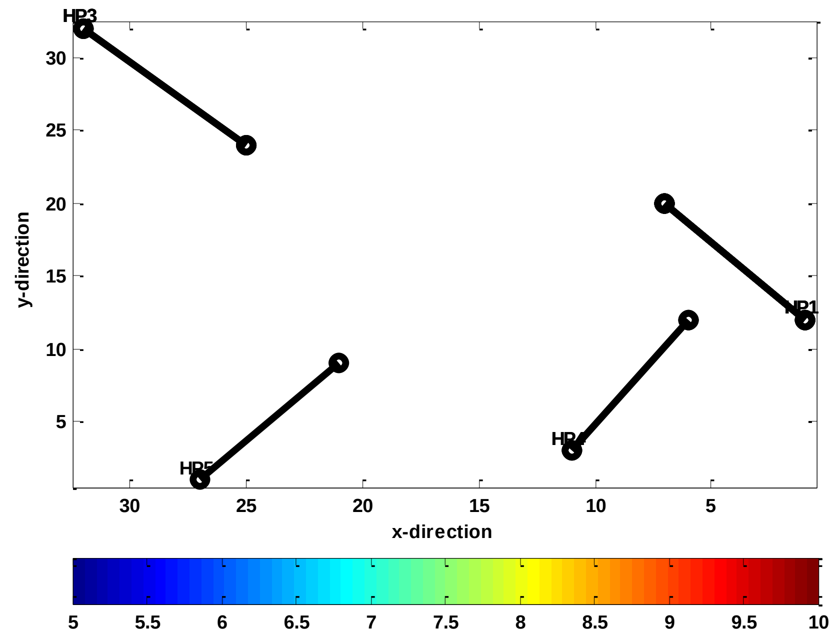
(c)



(d)

Figure 24: Best solution well location of SAGD model in 2D (x-y plane) for Case 3, (a) Layer 4 (b) Layer 5 (c) Layer 9, (d) Layer 10

Figure 24 shows that the horizontal injector and producer wells are placed at the heterogeneous sections of the reservoir. The reason behind that was that if both types of wells were placed in high permeable zone than there might be the possibility of severe water production or live steam coming from the production well, likewise if both types of wells placed at low permeability zones of reservoir there were a chance of low productive wells. So the optimization algorithm tries to find the region where both productivity and water production balances each other and gives maximum profit. The optimized vertical separation of 8.2 ft. was obtained for each well pair.

The best realization of the NPVs and objective function obtained from the three different cases for SAGD is shown in Figure 25, and Figure 26 respectively. The plots of NPV indicates that the Case 2 performed slightly better than Case 3. The Case 3 outperformed in terms of objective function for all cases, but with lower net present value than Case 2. Case 2, 3 indicate continuously improving trend of NPV. The well spacing constraint were satisfied in all the cases studied. Figure 27 and Figure 28 shows the median realization for NPV and objective function of all three cases for SAGD model respectively. Also, the results show better performance of Case 2 in NPV plot. The worst realization shows the better performance of Case 3 than Case 2 in Figure 29 and Figure 30. In all the cases studied, it seems promising that the optimization of well control and well location simultaneously rather than optimizing well location alone. The optimizer puts injector and producers very close to each other in Case 3 having the vertical separation of 8.2 ft. Also, four out of five injectors were having zero rates. This could be the possible reason for having better performance of Case 2 over Case 3. Also, it can be inferred from the results that there is little significance of optimizing vertical separation in SAGD operation but it was not further studied.

Figure 31 shows the net present value obtained in each case of SAGD process that are presented for different realization. It can be seen that the Case 2 performed better in all realization except first. Also, there were large variation of net present value in Case 2 and 3.

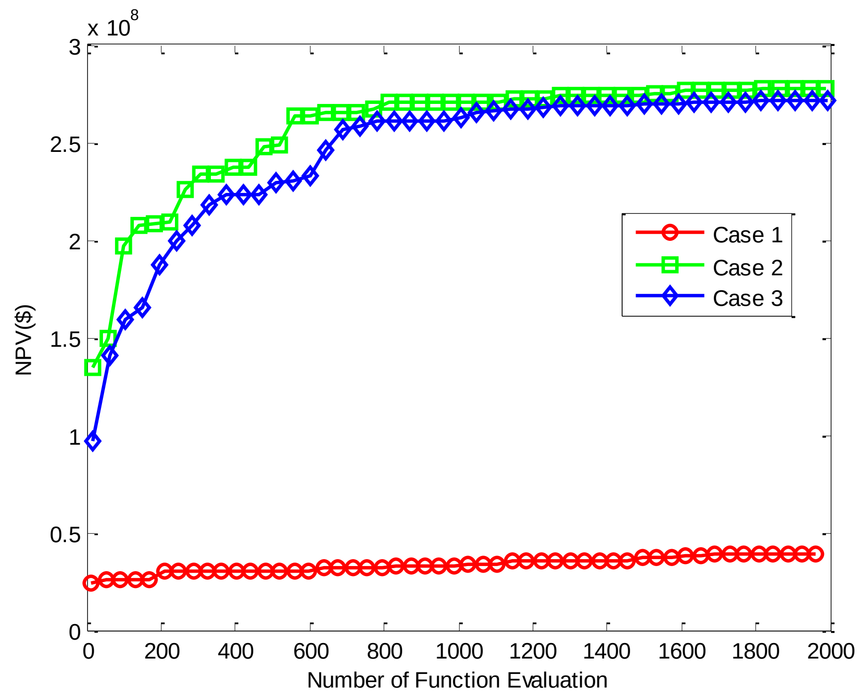


Figure 25: Best Solution of NPV for Different SAGD Cases

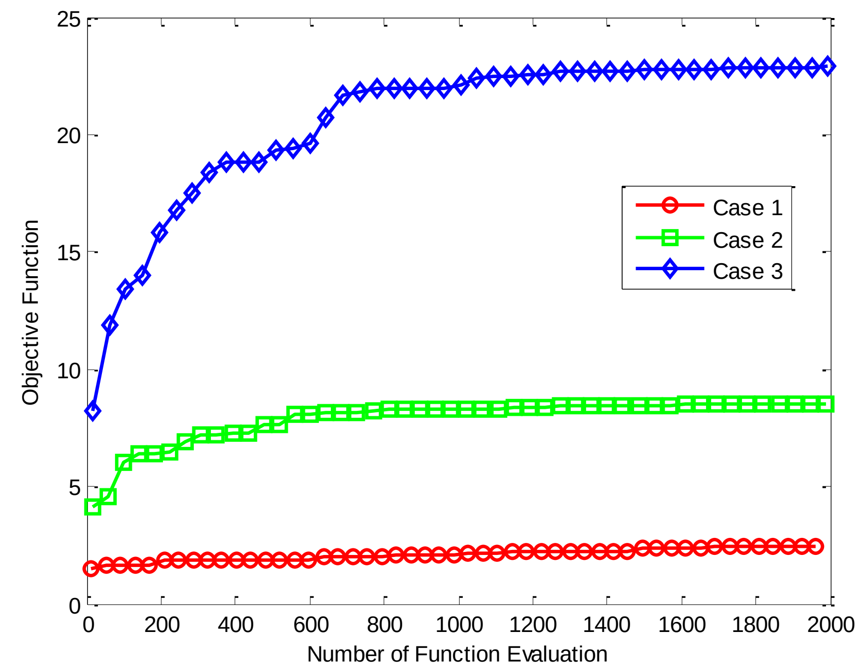


Figure 26: Best Solution of Objective Function of Different SAGD Cases

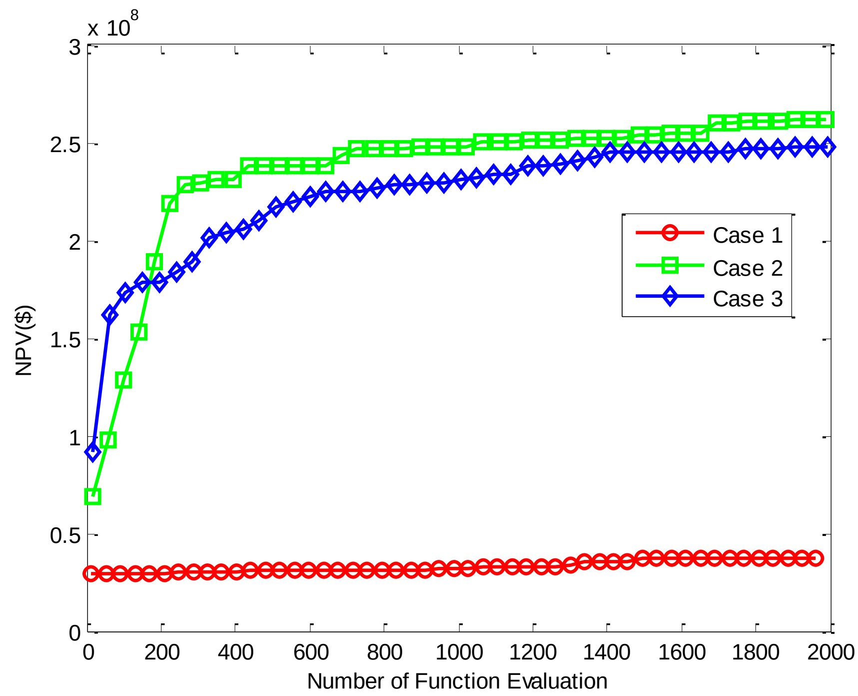


Figure 27: Median Solution of NPV for Different SAGD Cases

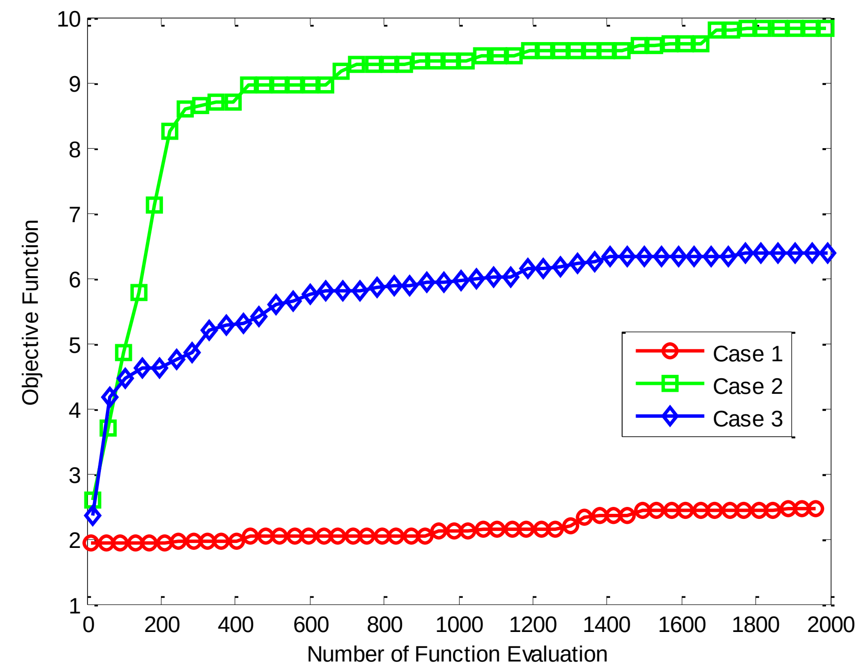


Figure 28: Median Solution of Objective Function of Different SAGD Cases

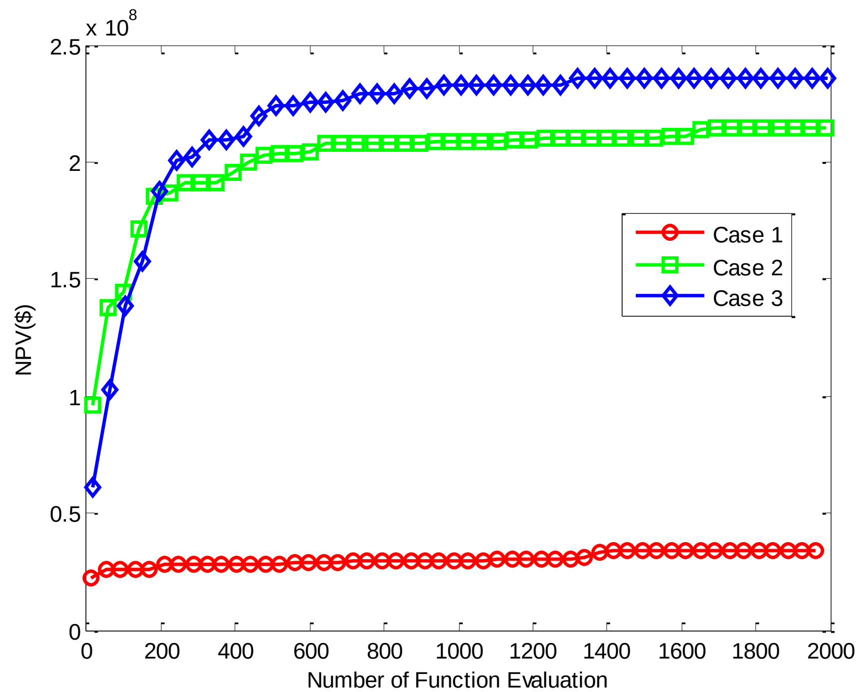


Figure 29: Worst Solution of NPV for Different SAGD Cases

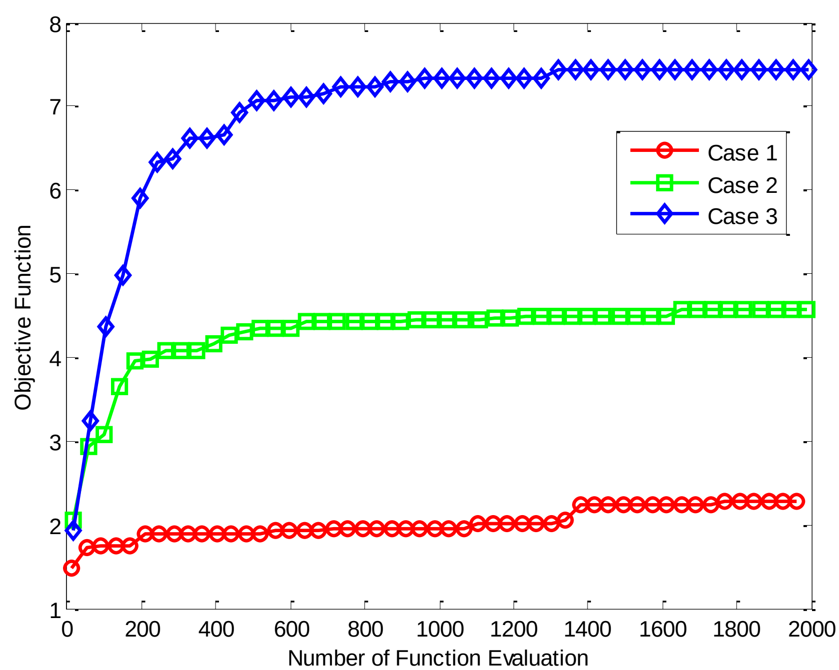


Figure 30: Worst Solution of Objective Function of Different SAGD Cases

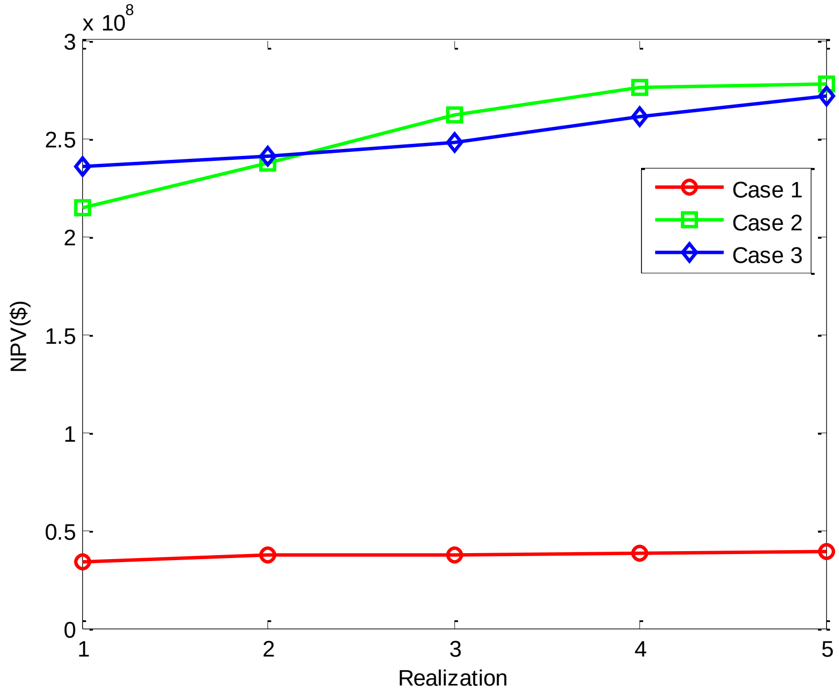


Figure 31: Comparison of different realization in SAGD

Figure 32 shows the net present value with respect to function evaluations performed to find the optimum solution for different realization of Case 1 in VAPEX. It can be seen from the plot that the second realization gave the best net present value (105 MM$) and the first realization was found to be median of the five realization which gave a net present value of (99 MM$) whereas the worst solution obtained in fifth realization having the net present value of (94 MM$).

Figure 33 shows the optimal horizontal well locations pairs in VAPEX Case 1, which gave the best result in terms of net present value. Figure 34 shows the 2-D view of the horizontal wells in each layer with permeability distribution.

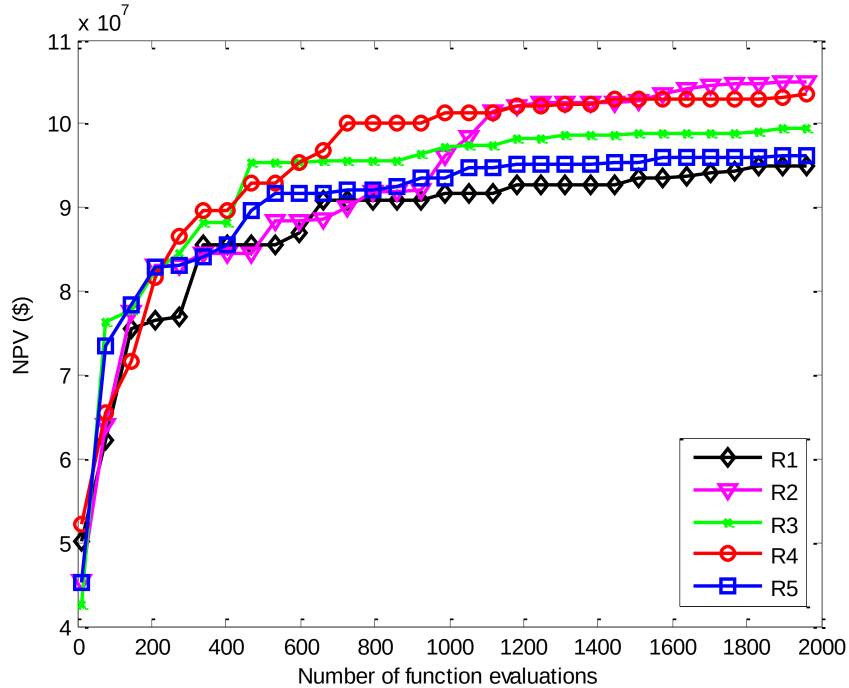


Figure 32: NPV comparison of different realization of Case 1 in VAPEX

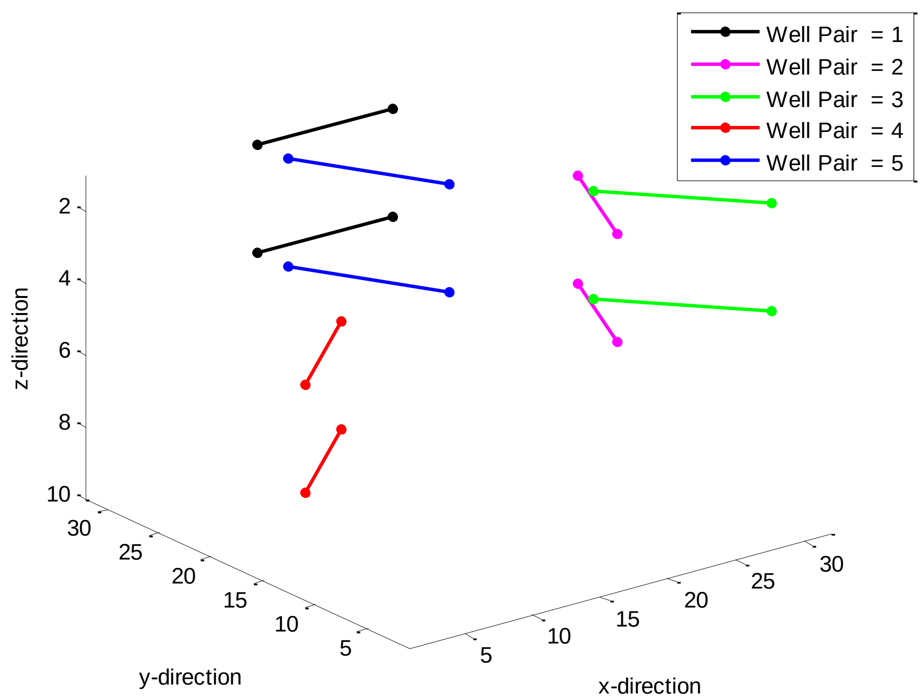
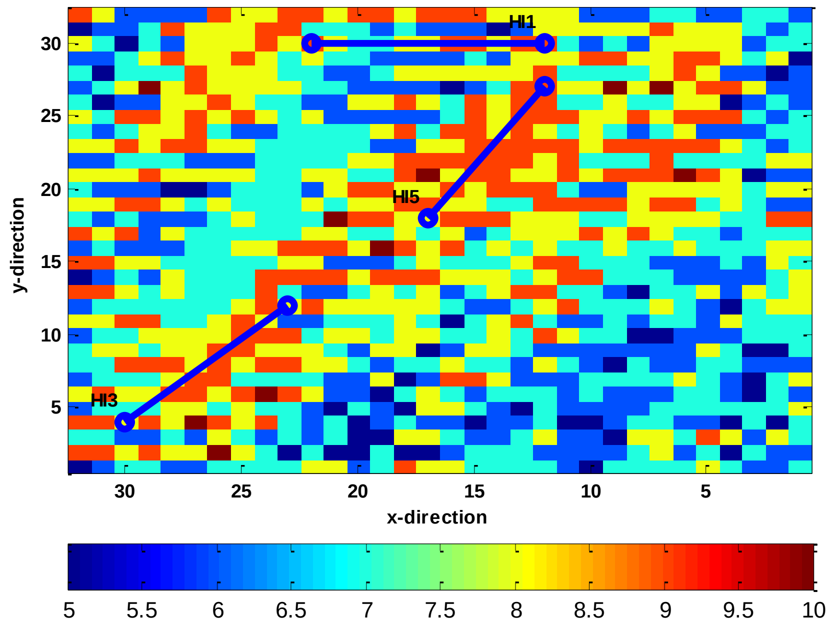


Figure 33: Well location representation of VAPEX best solution in 3D, Case 1


HI1
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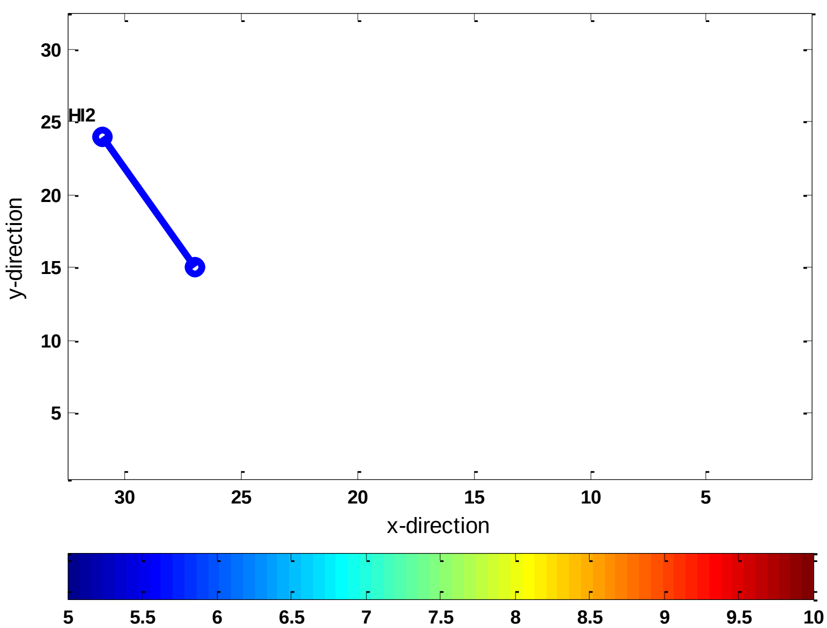
(a)


HI2
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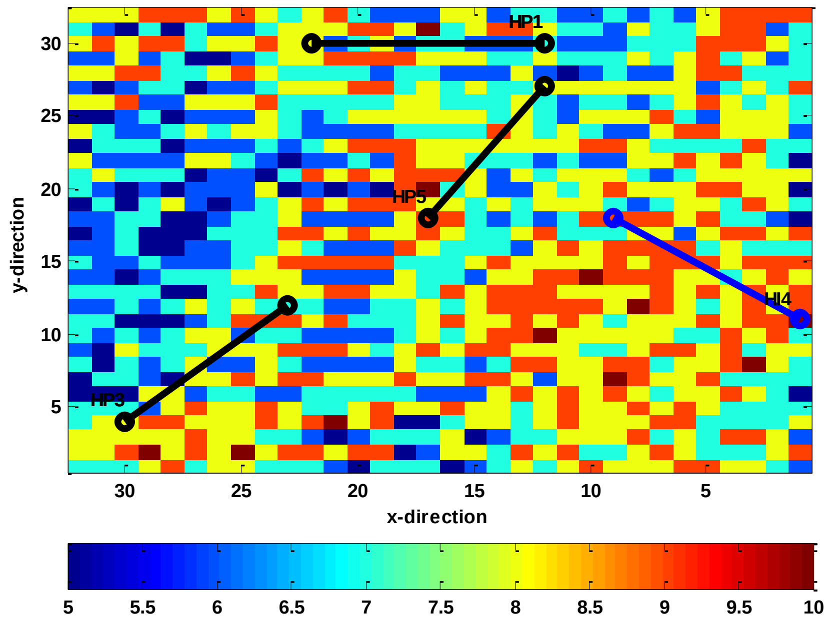
(b)


HP1
HP5
HI4
HP3
y-direction
x-direction
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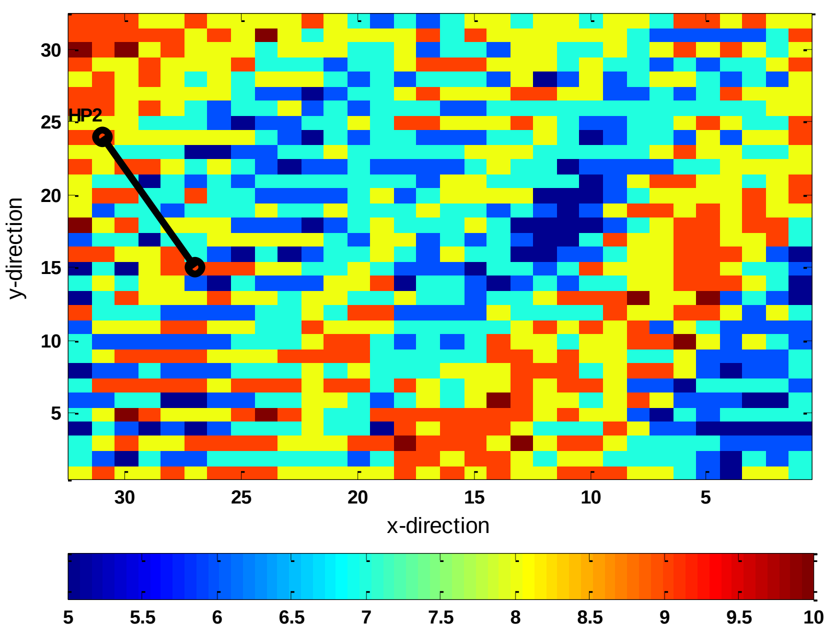
(c)


HP2
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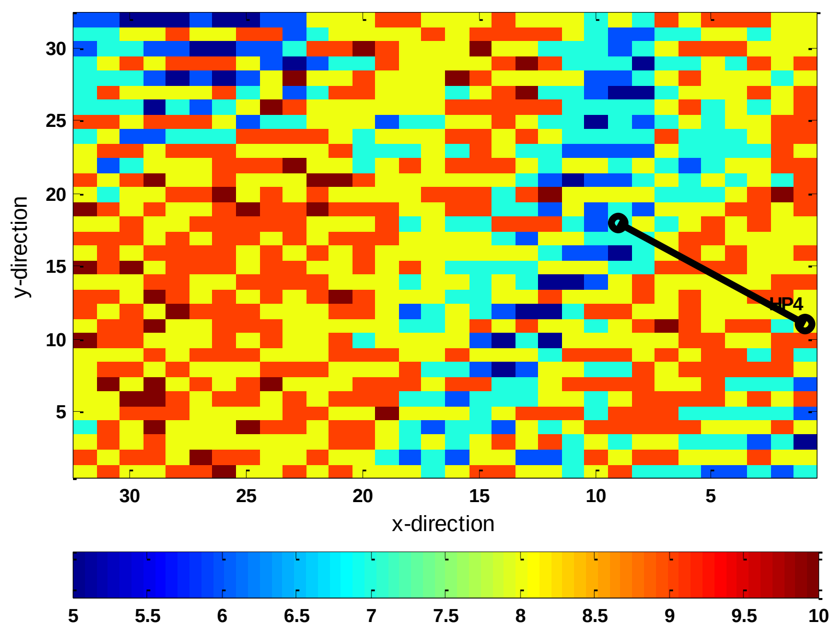
(d)



(e)

Figure 34: Best solution well location of VAPEX model in 2D (x-y plane) for Case 1, (a) Layer 1 (b) Layer 3 (c) Layer 4, (d) Layer 6, (e) Layer 7

It was observed that horizontal injector and producer wells were placed at the heterogeneous sections of the reservoir. It is due to the fact that if both types of wells are placed at a high permeable zone than there is a chance of severe gas production or solvent comes from the production well, similarly if both types of wells are placed at very low permeability of the reservoir then there would be low productivity of well.

Figure 35 shows the net present value obtained with reference to function evaluations for different realization of Case 3 in VAPEX. The highest net present value (110 MM$) was obtained in the first realization, realization 5 offer the median net present value (105 MM$), and the fourth realization shows the lowest net present value (100 MM$).

For the best solution, the optimal horizontal well locations pairs in VAPEX Case 3 is presented in Figure 36. The 2-D plot of horizontal wells in each layer with permeability distribution was plotted to observe the spacing constraint. It was found that all the production and injection wells were well spaced. Figure 37 shows that the horizontal injector and producer wells were placed at the heterogeneous sections of the reservoir. The reason behind that was if both types of wells were placed in high permeable zone than there might be the possibility of severe gas production or solvent stream comes from the production well, likewise if both types of wells were placed at low permeability zones of reservoir there was a chance of low productive wells. The optimized vertical separation of 8.2 and 41 ft. were found for different well pairs.

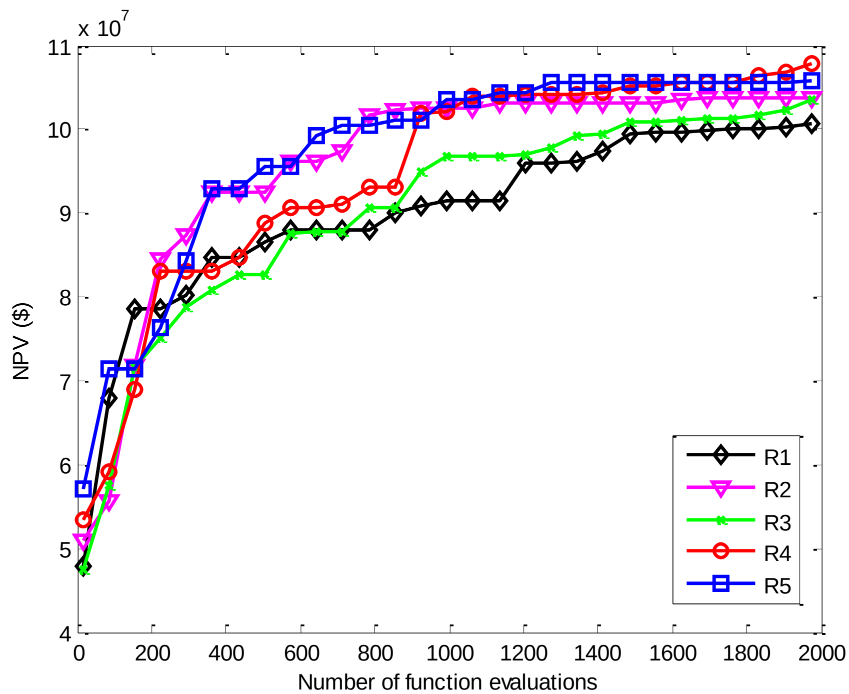


Figure 35: NPV comparison of different realization of Case 2 in VAPEX

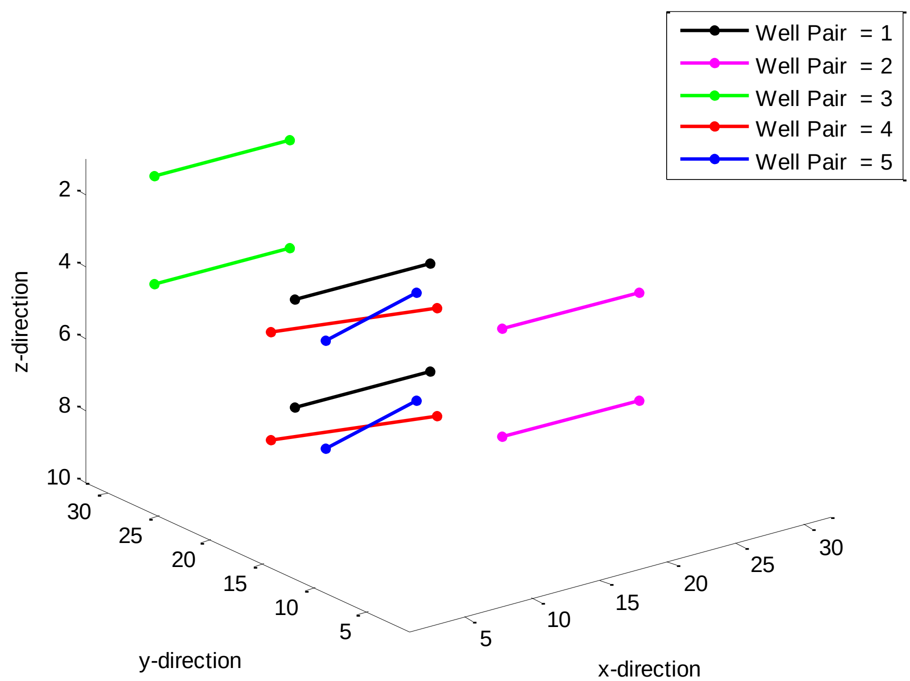
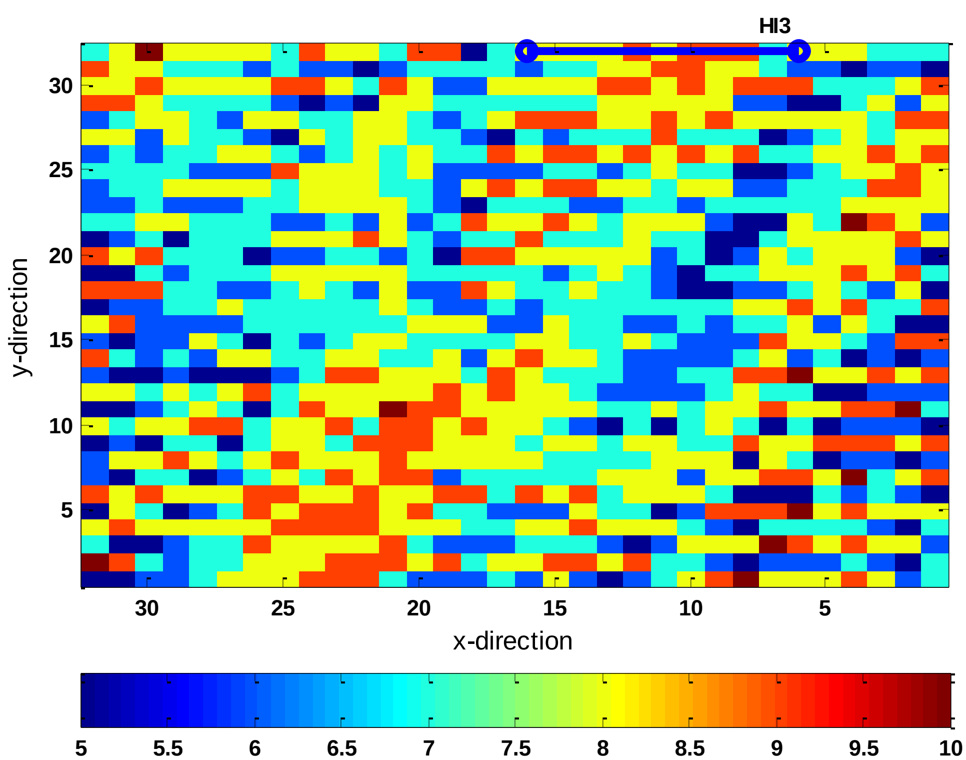
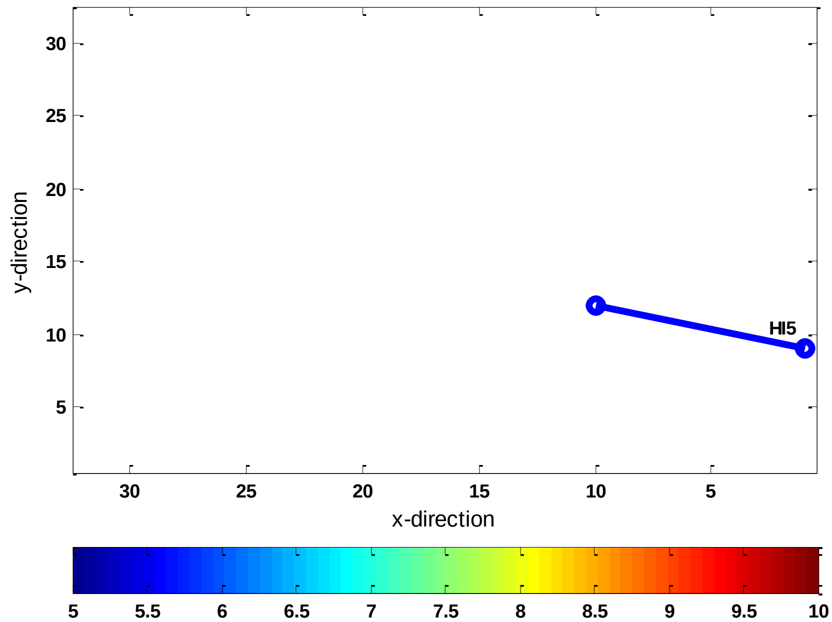


Figure 36: Well location representation of VAPEX best solution in 3D, Case 2



(a)



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y-direction
HI5
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x-direction
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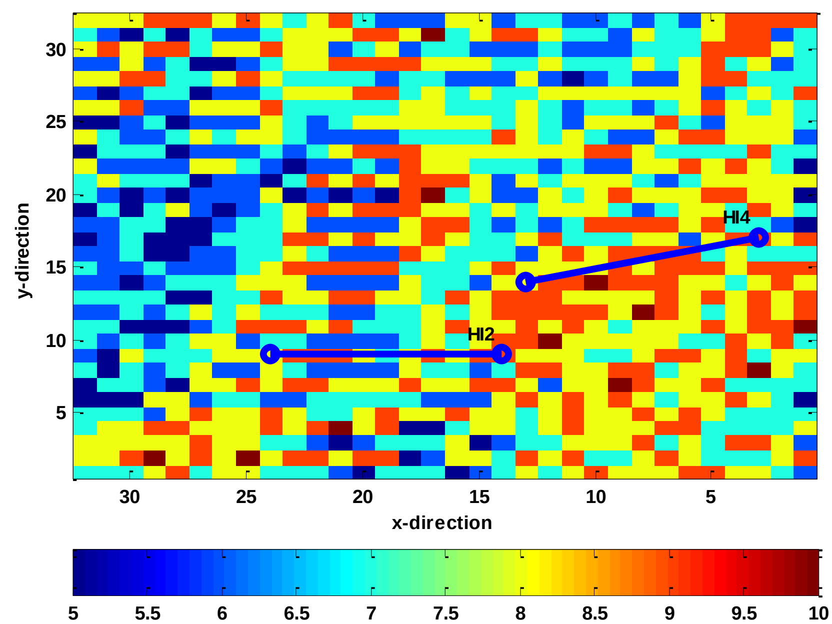
(b)



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y-direction
HI4
HI2
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x-direction
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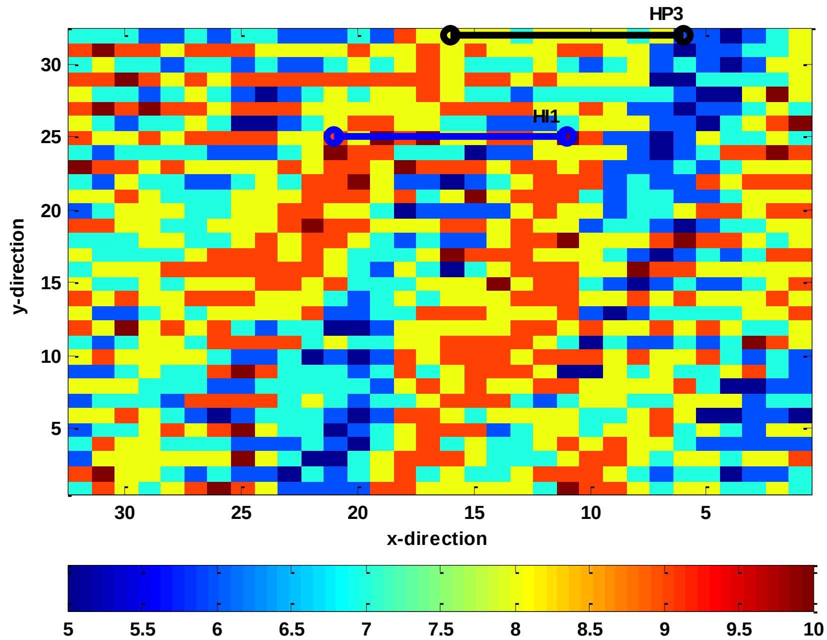
(c)



HP3
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y-direction
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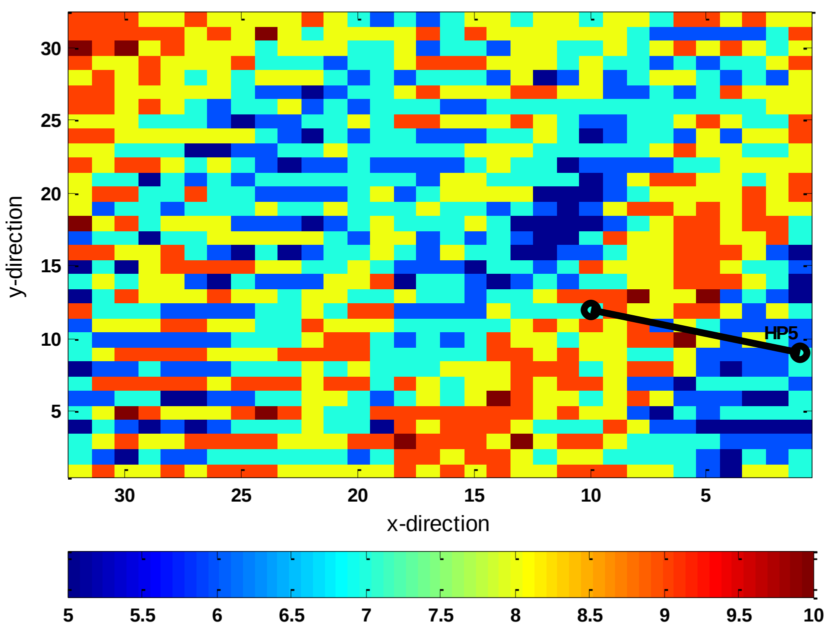
(d)



HP5
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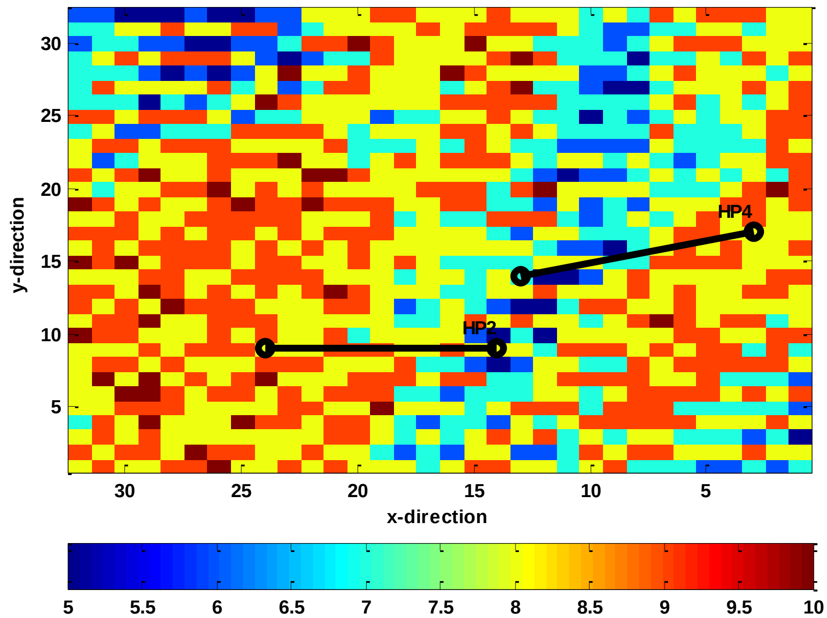
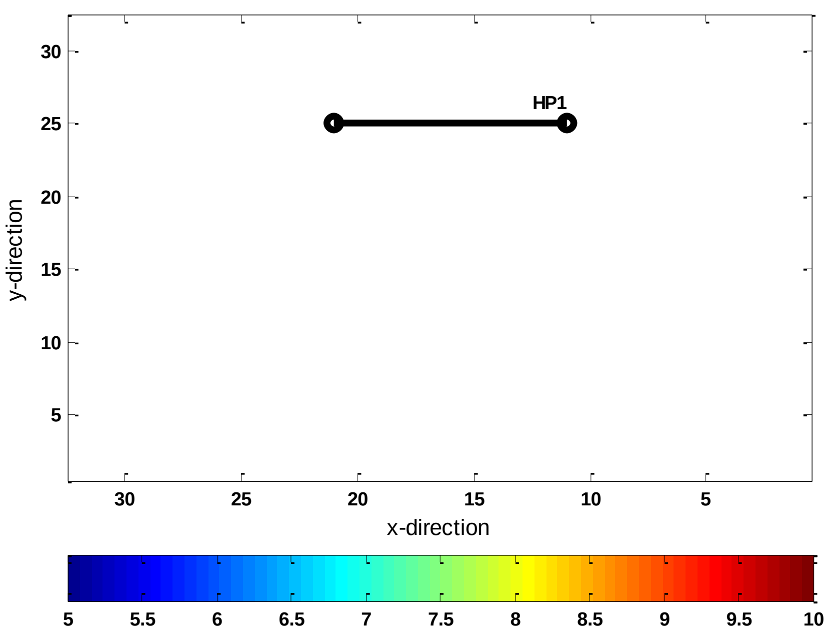
(e)



(f)



(g)

Figure 37: Best solution well location of VAPEX model in 2D (x-y plane) for Case 2, (a) Layer 2 (b) Layer 3 (c) Layer 4, (d) Layer 5, (e) Layer 6, (f) Layer 7, (g) Layer 8

Figure 38 shows the net present value versus function evaluations plot for different realization of Case 2 in VAPEX. It was seen that the fourth realization outperformed other realizations giving a net present value of (120 MM$), and the median net present value of (109 MM$) was found in the second realization, whereas the worst solution was obtained in the fifth realization with a net present value of (100 MM$).

The optimal horizontal well locations pairs of VAPEX for Case 2 is shown in Figure 39, which gave the best result in terms of net present value. Figure 40 shows the 2-D view of horizontal wells in each layer with permeability distribution.

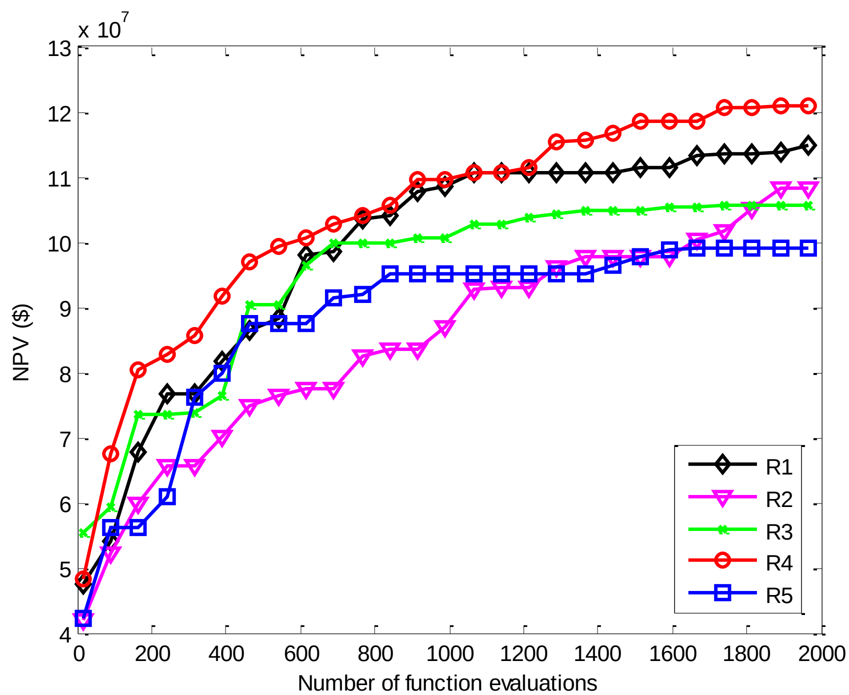


Figure 38: NPV comparison of different realization of Case 3 in VAPEX

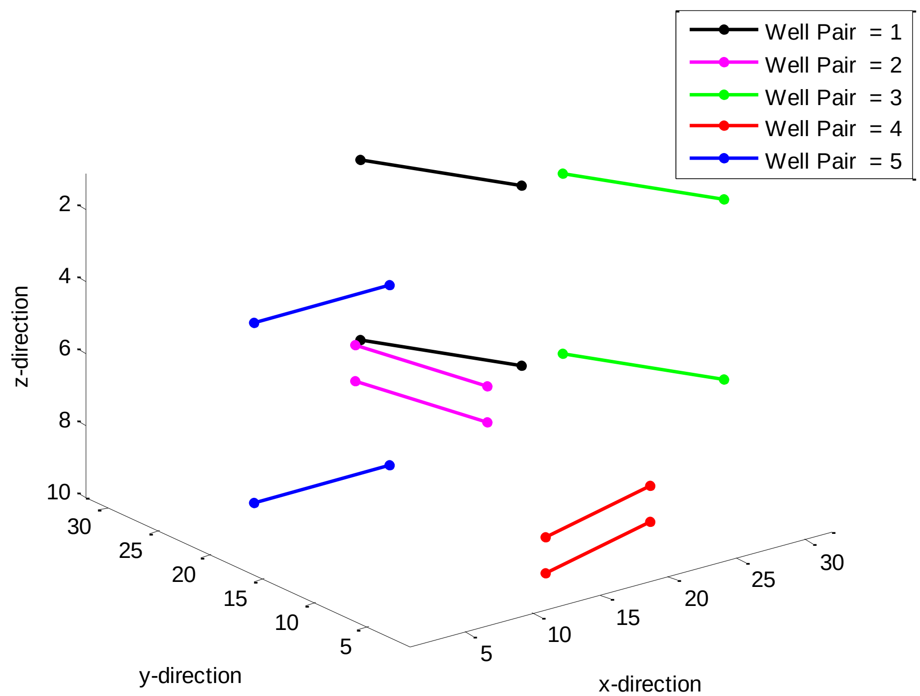
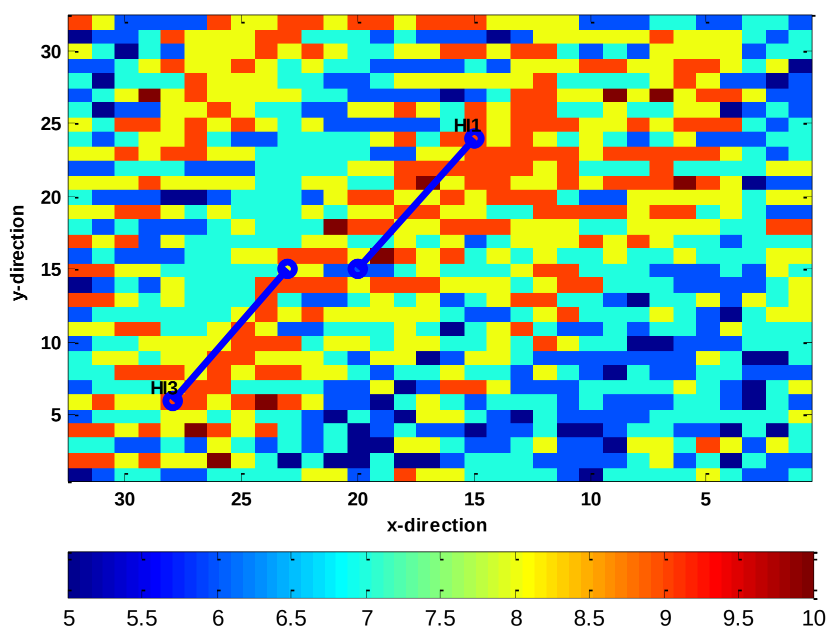
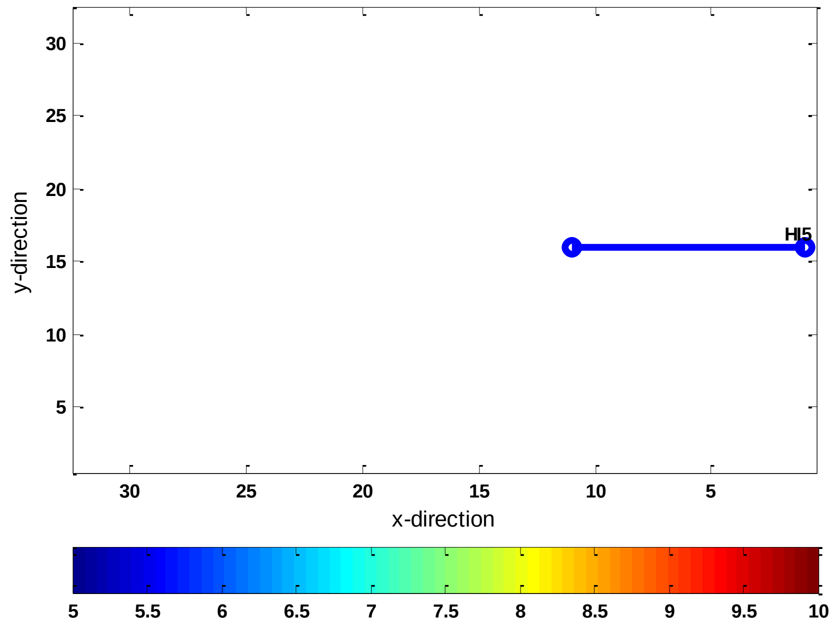


Figure 39: Well location representation of VAPEX best solution in 3D, Case 3



(a)



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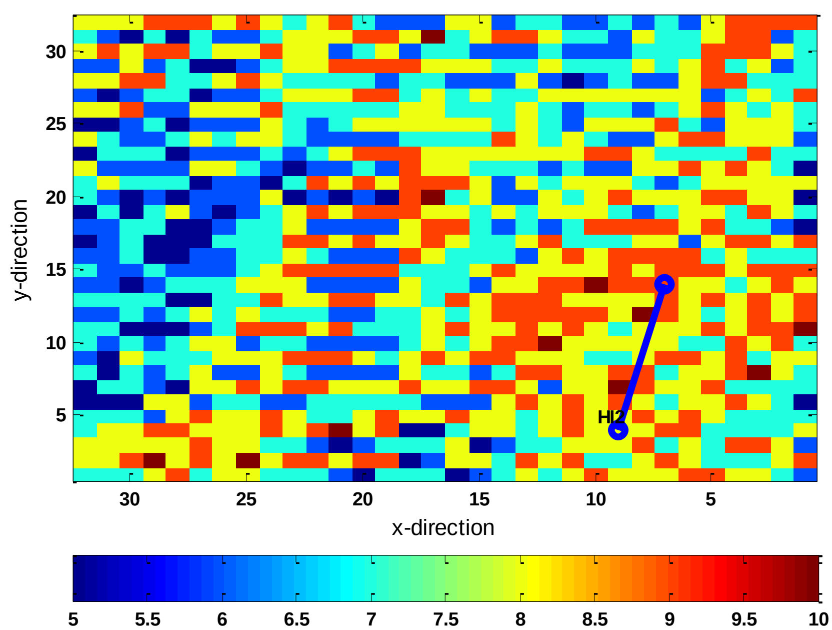
(b)



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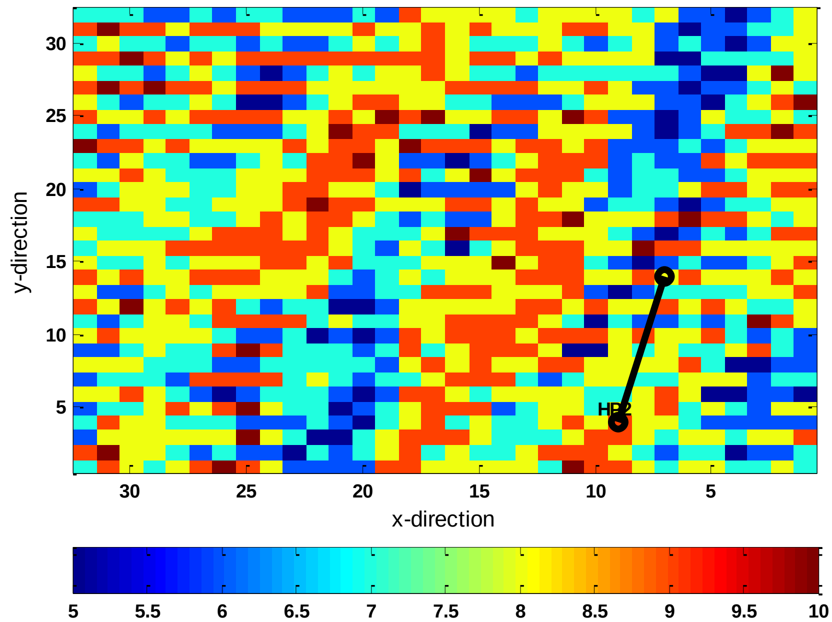
(c)



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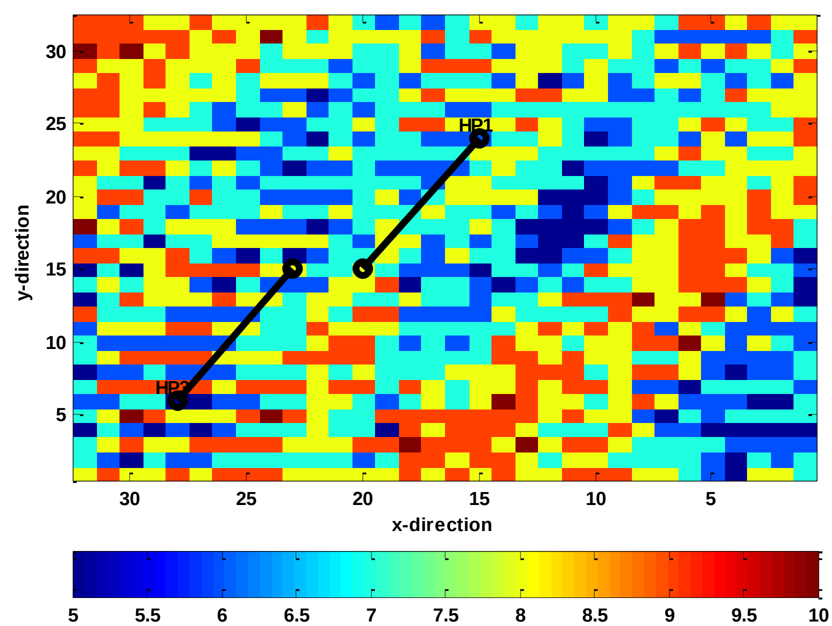
(d)



HP1
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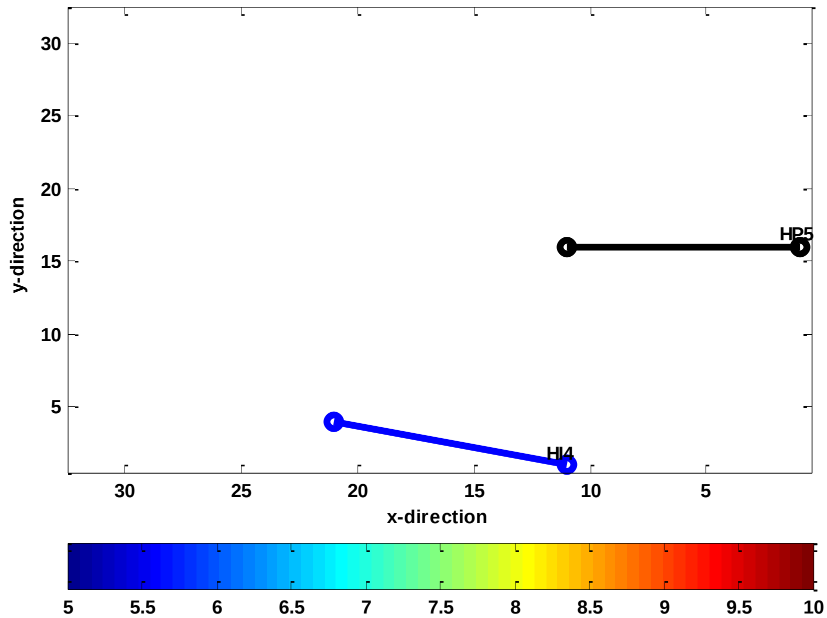
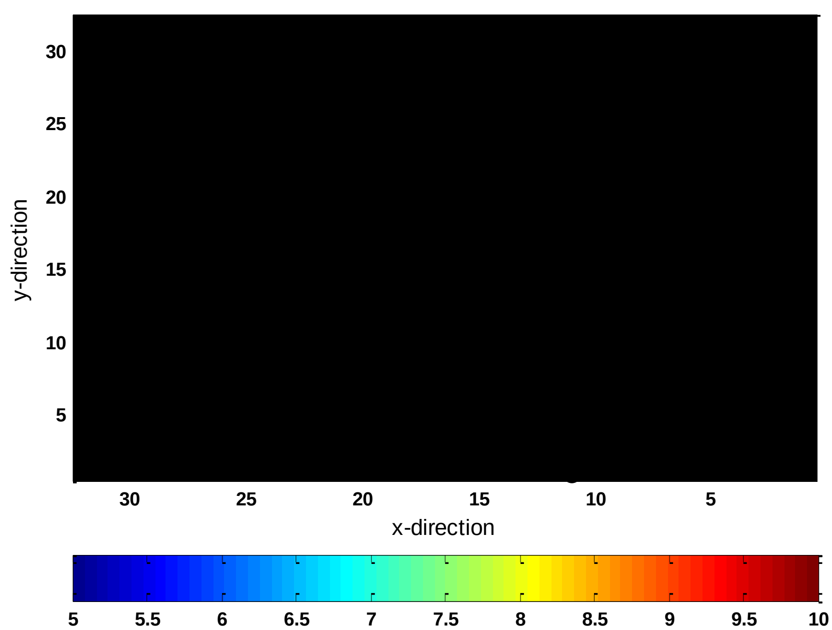
(e)



(f)



(g)

Figure 40: Best solution well location of VAPEX model in 2D (x-y plane) for Case 3, (a) Layer 1 (b) Layer 3 (c) Layer 4, (d) Layer 5, (e) Layer 6, (f) Layer 8 (g) Layer 9

The result shows that the horizontal injector and producer wells were placed at the heterogeneous sections of the reservoir. It is due to the fact that if both types of wells were placed at the high permeable zone than there is a possibility of severe water production from the producers, similarly if both types of wells were placed at very low permeability of the reservoir then there would be low productivity of well.

The best realization of NPVs and objective function obtained from the three different cases for VAPEX is show in Figure 41, and Figure 42 respectively. The plots of NPV indicates that the Case 2 performed slightly better than Case 3. The Case 3 outperformed in terms of objective function for all cases, but with lower net present value than Case 2. Case 2, 3 indicates a continuously improving trend of NPV. The well spacing constraint were satisfied in all studied cases. Figure 43 and Figure 44 shows the median realization for NPV and objective function of all three cases for VAPEX model respectively. Also, the results show better performance of Case 2 in NPV plot. The worst realization shows the better performance of Case 3 than Case 2 in Figure 45 and Figure 46. In all cases studied, it seems promising the optimization of well control and well location simultaneously rather than optimizing well location alone.

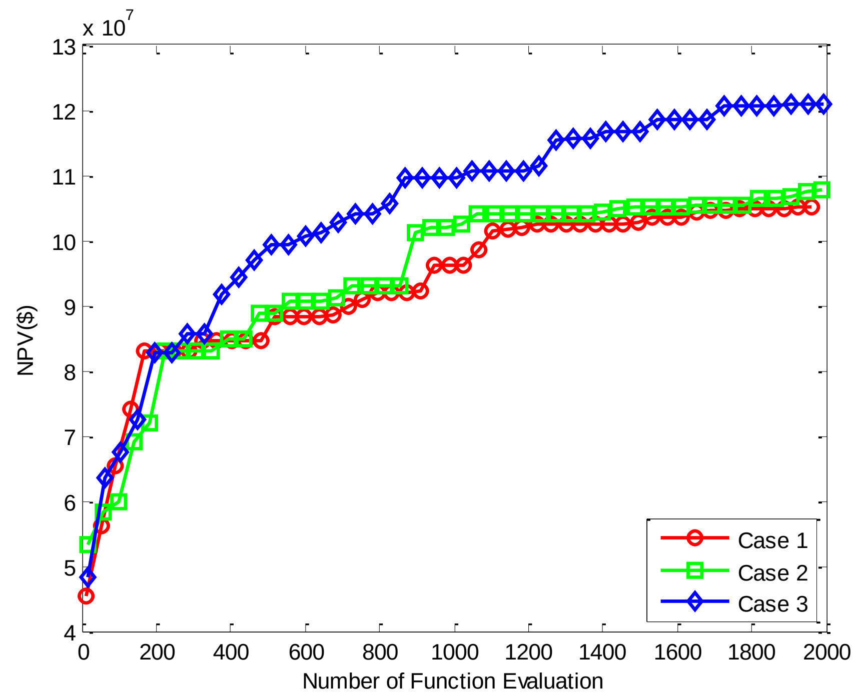


Figure 41: Best Solution of NPV for Different VAPEX Cases

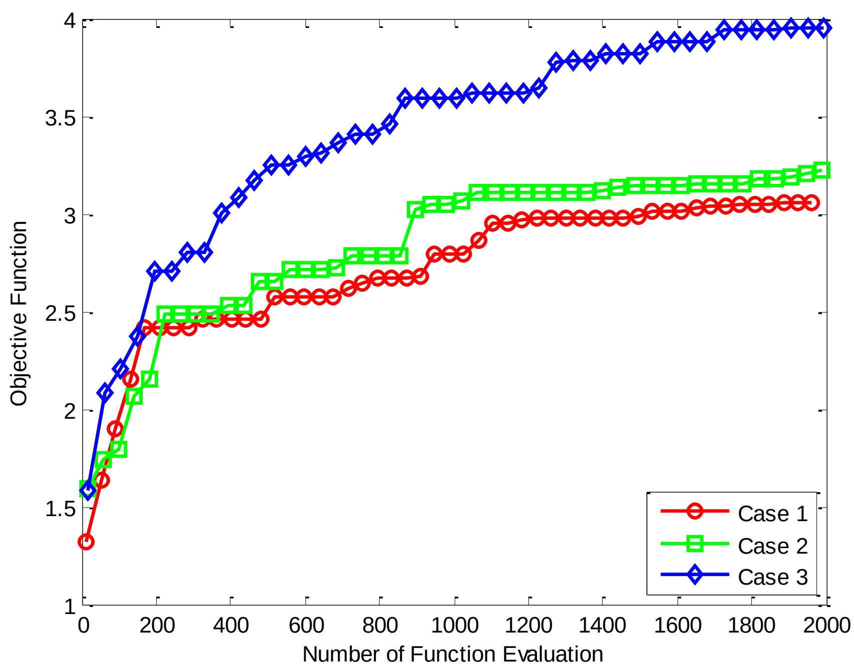


Figure 42: Best Solution of Objective Function of Different VAPEX Cases

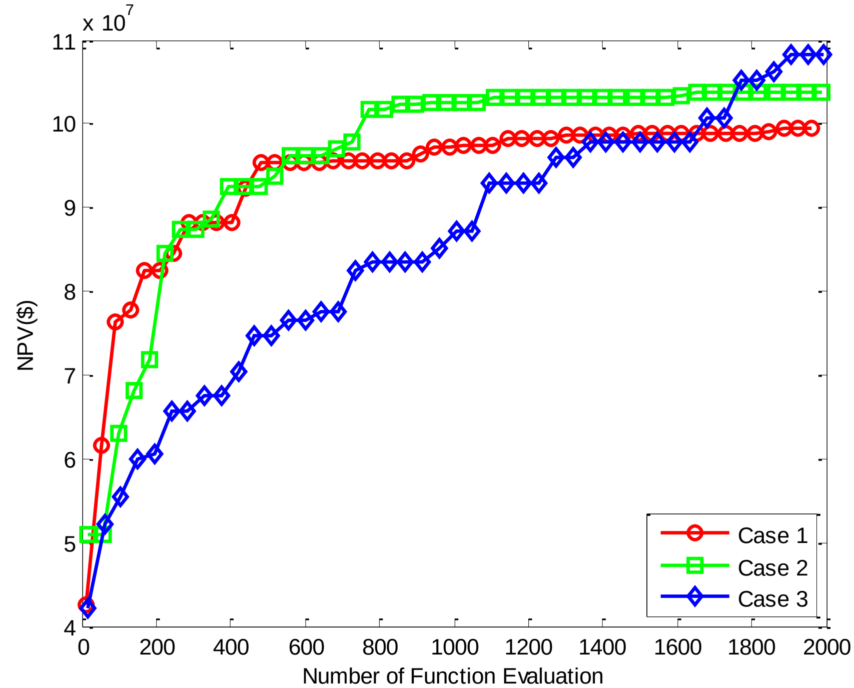


Figure 43: Median Solution of NPV for Different VAPEX Cases

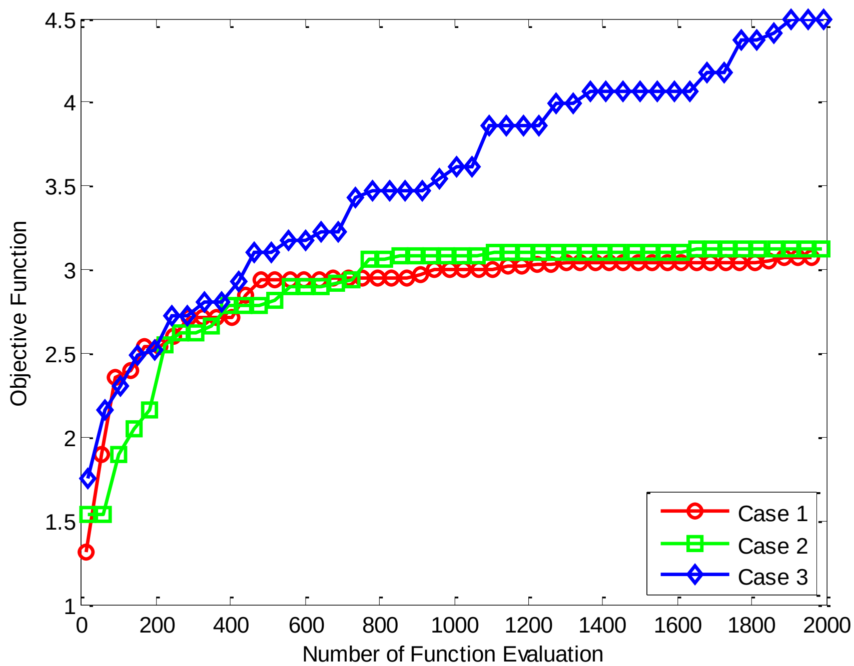


Figure 44: Median Solution of Objective Function of Different VAPEX Cases

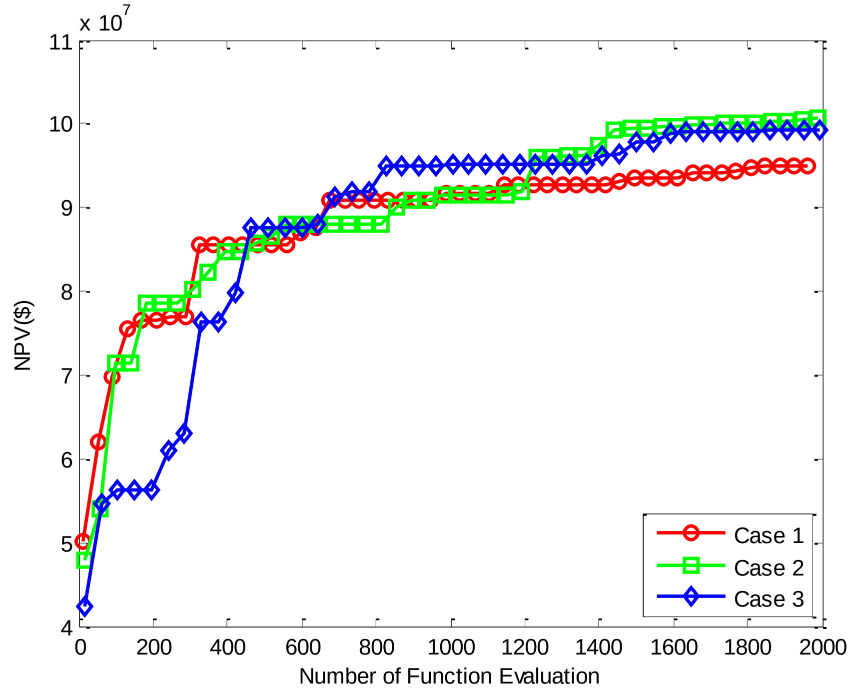


Figure 45: Worst Solution of NPV for Different VAPEX Cases

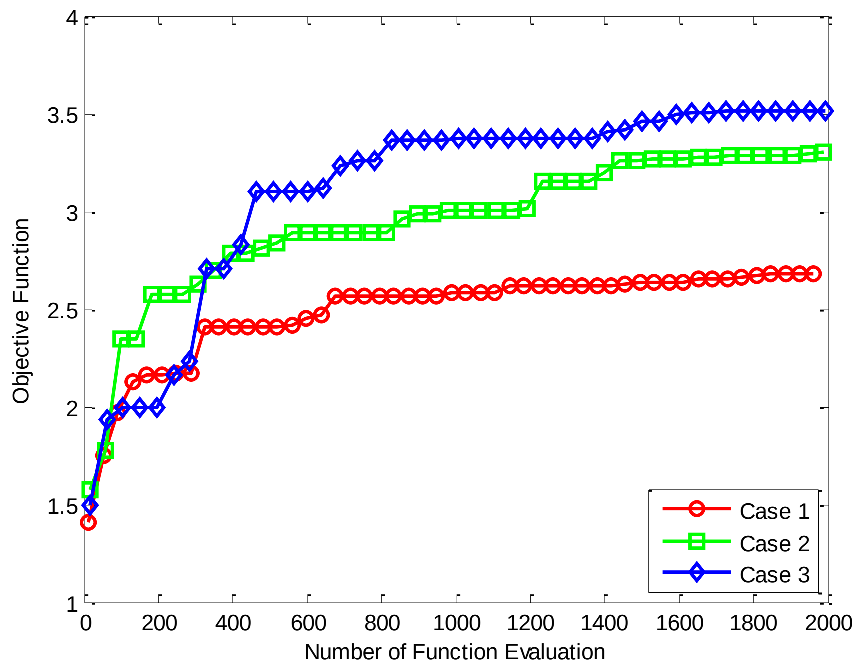


Figure 46: Worst Solution of Objective Function of Different VAPEX Cases

Comparison of SAGD and VAPEX Process

The comparison between SAGD and VAPEX processes is discussed in this section. The comparison were based on the simulation results obtained from the optimization process. The simulation model of both models were identical and the important fluid and rock properties were kept same to make unbiased comparison. Figure 47 shows the comparison net present values obtained in Case 1 of both process. As expected, the performance of VAPEX process were observed to better than SAGD. In this case, only the well placement were optimized at a fixed defined well controls.

Figure 48 shows the performance of SAGD and VAPEX in Case 2. The plots shows the better performance of SAGD operations as compared to VAPEX process which is in contrary to our expectation. The heterogeneity present in both models could be one of the reason for low VAPEX performance as it was discussed by Jiang (1996). Also, in the Case 1 in which VAPEX performed better was operating at a defined well control which were not optimized. The performance of both operations is highly dependent on controls. The optimized parameters of both processes were listed in Table 3 for Case 2.

Figure 49 shows the comparison of SAGD and VAPEX processes in Case 3. The results were quite similar to the comparison results of Case 2. SAGD performance were better than VAPEX. The optimized parameters of both cases were presented in Table 4 for Case 3.

The results of total cumulative oil production and oil rate for each case of SAGD and VAPEX processes is presented in Figure 50 and Figure 51. It was noticed that the well rates used in Case 1 of VAPEX process is close to the optimized rates obtained in Case 2, it explains the better performance of VAPEX process over SAGD in Case 1.

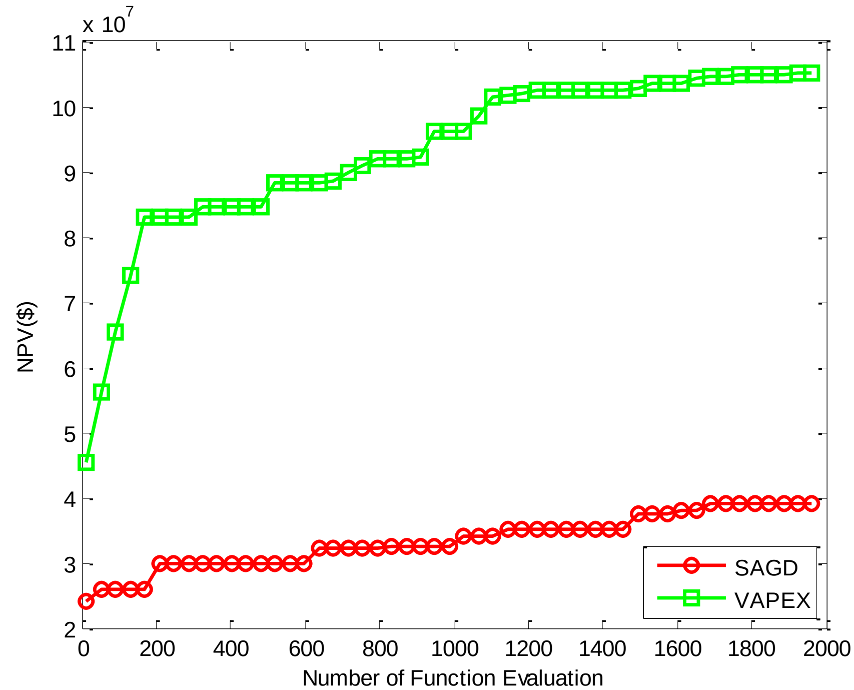


Figure 47: Best Solution of NPV Comparison of SAGD and VAPEX for Case 1

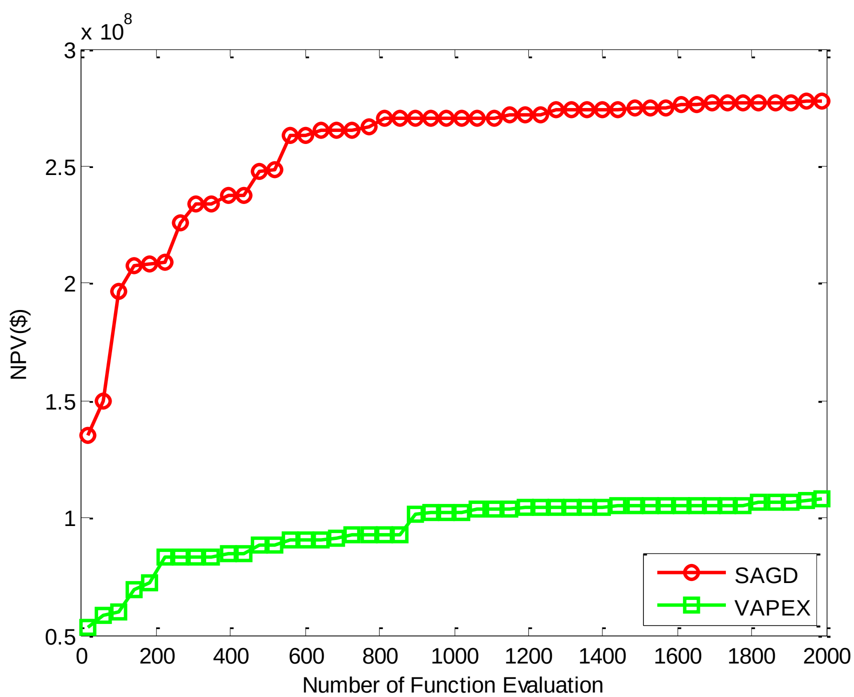


Figure 48: Best Solution of NPV Comparison of SAGD and VAPEX for Case 2

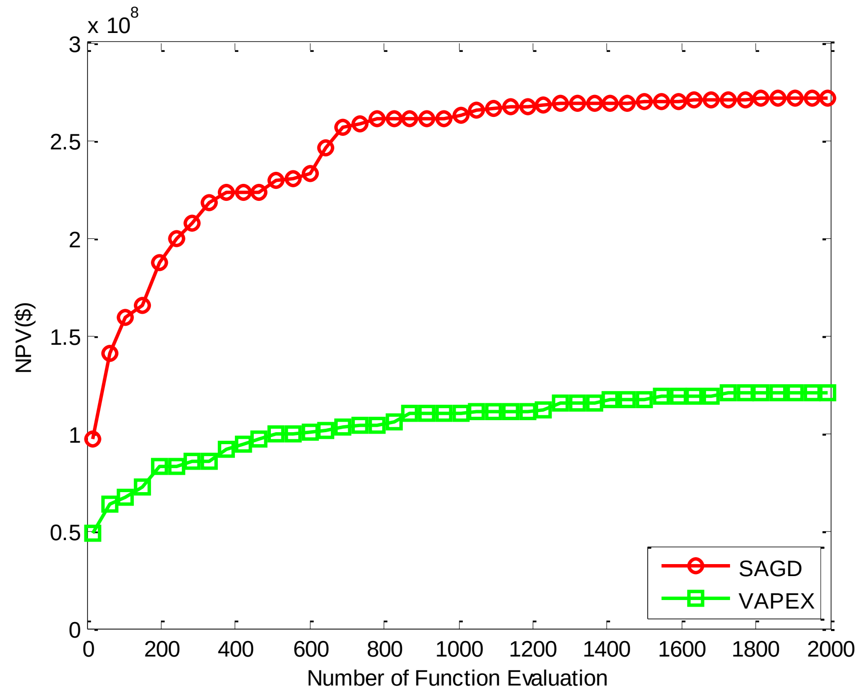


Figure 49: Best Solution of NPV Comparison of SAGD and VAPEX for Case 3

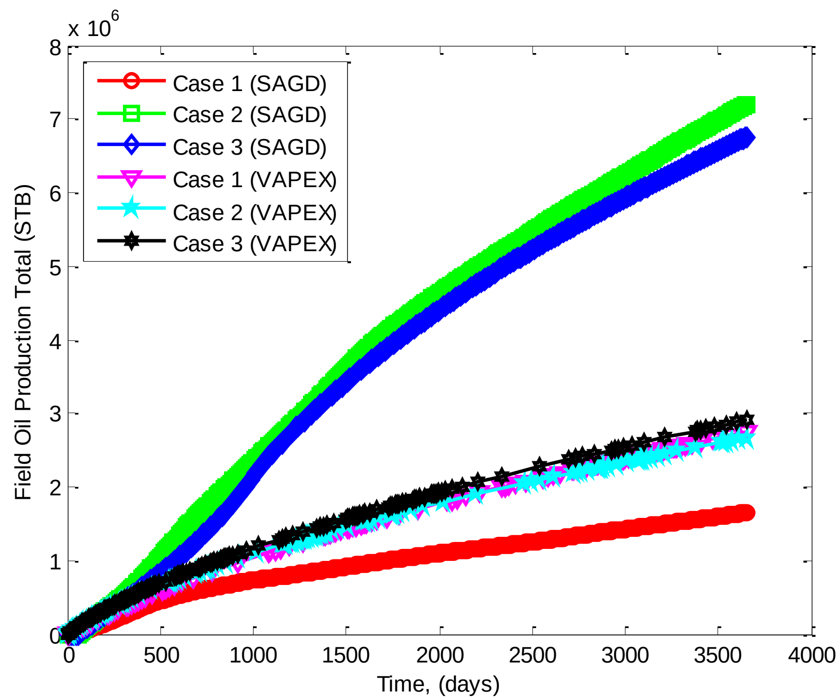


Figure 50: Cumulative Production for SAGD and VAPEX

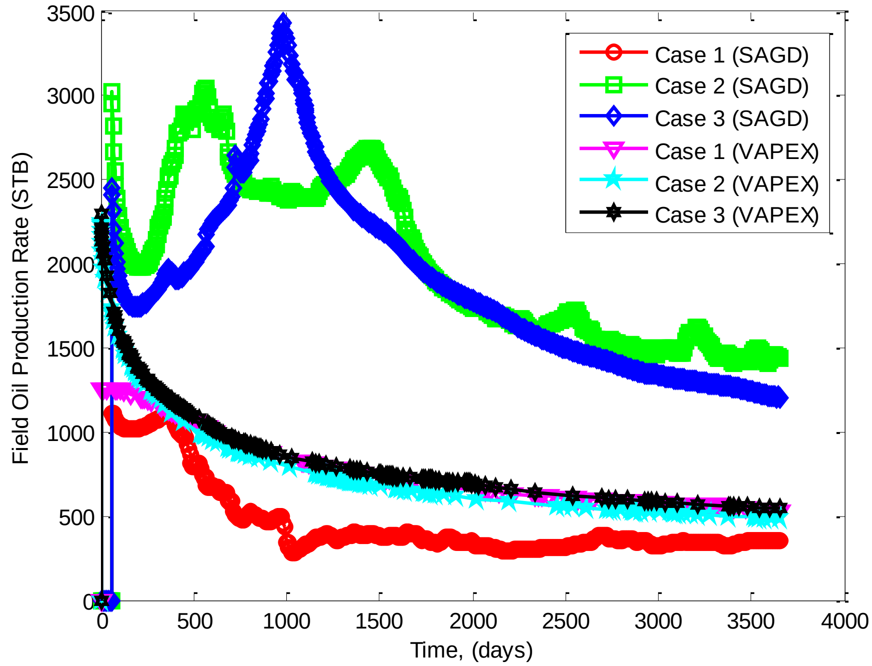


Figure 51: Oil Production Rate for SAGD and VAPEX

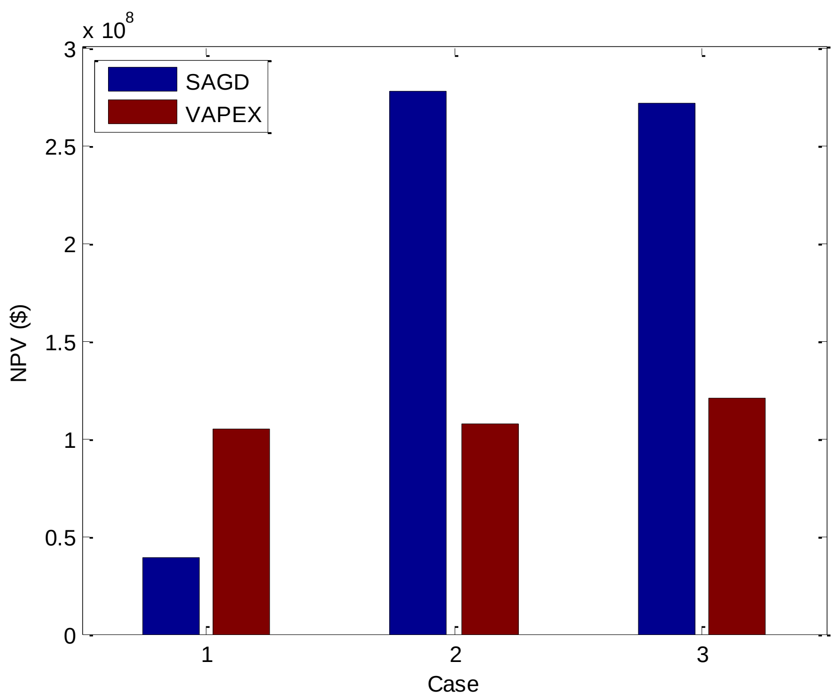


Figure 52: Comparison of Different Cases of SAGD and VAPEX for Best Solution

The bar graph of all three cases for both SAGD and VAPEX is plotted to summarize the discussion in Figure 52.

Table 3: Optimized Well Rates of SAGD and VAPEX for Case 2

Well	SAGD	VAPEX
	Rate (STB/D)	Rate (STB/D)
P1	1000	892
I1	120	784
P2	1000	276
I2	126	1000
P3	1000	853
I3	184	774
P4	977	279
I4	79	632
P5	526	413
I5	4	24

Table 4: Optimized parameters of SAGD and VAPEX for Case 3

Well	SAGD		VAPEX	
	Rate (STB/D)	Vertical Separation (ft.)	Rate (STB/D)	Vertical Separation (ft.)
P1	863	8.2	431	41
I1	0		835	
P2	1000	8.2	266	8.2
I2	0		745	
P3	1000	8.2	915	41
I3	117		1000	
P4	807	8.2	593	8.2
I4	0		1000	
P5	905	8.2	811	41
I5	0		1000	

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

[redacted] Conclusions

Based on the results and discussion presented in Chapter 5, it is evident that the stochastic optimization performed well in all the cases presented for SAGD and VAPEX processes.

- In this study, we have presented a method to enforce minimum well spacing constraint for horizontal well placement optimization. A well-spacing constraint method based on the penalty approach was used to constrain the wells in the reservoir. Constraining circles and ellipses were placed around vertical section and horizontal wells, respectively, to indicate the areas within which no other wells should be placed. The methodology proves to perform well in all cases presented for both processes.
- Particle swarm optimization (PSO) is successfully implemented to optimize the parameters in Well Placement Optimization (WPO) and Well Control Optimization (WCO). One sample applications were presented to show the effectiveness of the method on both SAGD and VAPEX processes.
- In SAGD, the performance in term of net present value (NPV) of Case 2 is better than other Case 1 and Case 3.
- In VAPEX, the net present value (NPV) obtained in Case 3 outperformed the values of NPV in Case 1 and Case 2 as expected.

- It is also noted that the placement of injector and producer is greatly influenced by the permeability distribution in the reservoir.

The comparison of SAGD and VAPEX processes were conducted based on NPV obtained in each of the discussed cases.

- In Case 1, the results shows better performance of VAPEX over SAGD. It was noticed that the well rates used in Case 1 of VAPEX process is closed to the optimized rates obtained in Case 2, it explained the better performance of VAPEX process over SAGD in Case 1.
- In Case 2 and 3, the NPV outcomes indicates better performance of SAGD on VAPEX.

[redacted] Recommendations

Based on the literature survey and the insights from this research work, we propose the implementation of the following items to achieve a more powerful optimization framework:

- To implement the optimization of different well configuration of horizontal wells for example curved well that can be represented by a circular formula, snaky shape well, or deviated well etc.
- To apply 3D well spacing constraint for horizontal well placement optimization problem.
- To consider the local grid refinements around the horizontal section of well with the application of efficient proxy methods to reduce the additional simulation cost.

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